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STOCHASTIC MODELING OF A MAGNETIC RESONANCE IMAGING PERFORMANCE AND COST IN A LARGE TEACHING HOSPITAL

by

Reginald Anthony Narsing

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ABSTRACT

Healthcare in Canada is undergoing rapid changes in an attempt to streamline costs, increase process efficiencies, and maximize throughput. Unfortunately, deep cuts have dampened attempts to upgrade capital assets. A shrinking capital fund allows funding for a select number of capital projects. As a result, hospital departments are forced to compete for scarce resources by demonstrating need using comprehensive objective analyses. The Magnetic Resonance Imaging (MRI) Section of a large teaching hospital, in particular, faces acute system performance and capital budgeting problems. These problems include a lengthy wait list, rising operating costs, low equipment utilization, decreased throughput, increased downtime, and overall drop in operating efficiency. The current system and methods in place are inadequate to maintain an efficient and economical operation of the MRI system.

In this research study, the author develops structural MRI options to solve the system performance problems within the limiting constraints in this teaching hospital. Stochastic models of these MRI options are also developed to capture the complex variabilities in these options. The Monte Carlo method is used to solve these stochastic models by simulating random values from probability density functions of sensitive random variables. These sensitive random variables are selected through variance sensitivity analysis using functional moment methodology. The stochastic models are validated with historic data on current MRI operations and similar operations within the same Capital Health Region. Analysis of the results shows that upgrading the existing 1.5 Tesla (T) MRI and adding a smaller 0.25T version is the best choice among the 28

structural design options. By this upgrade, the MRI system performance can be increased by 150 percent from 50 to 126 operating hours per week. Furthermore, equipment utilization is expected to increase from 35 to 88 percent. Annual MRI exams increase from 4,725 to 11,907 resulting in decreases to waiting period from six to two months. The cost per exam decreases from $567 to $350 resulting in a total savings of $2.6 million annually. The probability of achieving $350 per exam is 53 percent. The opportunity cost for doing nothing is $217 per exam as compared to the UES option.

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NOMENCLATURE

AEC	annual equivalent cost
γ_1	labor cost variable
γ_2	supplies cost variable
γ_3	capital cost variable
γ_4	fixed cost variable
γ_5	inflation adjusted pre-tax discount rate
γ_6	renovation cost variable
γ_7	salvage value cost variable
MedFee	interpretation fees paid to radiologists to examine scan
MedSal	salary paid to a medical physicist
PrePay	incremental adjustment to salary per union agreement
RegEst	represents regular salary payment
Admin	represents administration costs
EmpBen	benefit/ fringe payments
MedSurg	purchases of medical & surgical supplies
ConMed	purchase of dye used as a tracer, once injected into the body
Drugs	drug utilization for various applications, i.e. sedating patients
Radiology	film purchases, lens replacement etc.
Lab	laboratory tests
Food	purchase of catering services for meetings
HouseKpg	charges arising from housekeeping services
OffSupp	purchase of general office supplies
GenSupp	miscellaneous purchase of supplies
Comm	charges for communicating devices and services
TravExp	expenses due to travel, i.e. site visits, conferences
ProfFee	payment of profession association fees
EducPrg	educational training courses

PurServ	miscellaneous purchase of services
ConMain	purchase of contract maintenance
MinCap	minor capital purchases
CapEqp	major capital equipment purchases
Fixed	charges include payments for insurance, rent, utilities
Po	initial capital cost at year 0
Uc	upgrade cost
Rent	charges related to occupancy
Ins	insurance coverage
Util	utilities consumed such as water, power, and gas
Inf	expected inflation rate
Prr	pre-tax discount rate
n	project planning horizon
Rc	renovation cost
Sv	salvage value
E[AEC]	expected value of the annual equivalent cost
VAR[AEC]	variance of the annual equivalent cost
BIAS	random noise about E[AEC]
α	decision space
λ	decision strategy
$\beta(\alpha;\mu,\sigma)$	lost opportunity cost function
$\psi(\lambda;\mu,\sigma)$	risk associated with lost opportunity function
S	sample space
μ	population mean
σ	population standard deviation
PDF	probability distribution function
a_i	i^{th} design option
UES	upgrade exiting system
CAT	computed axial tomography

CAR	contract another hospital
CPO	contract private operator
LCE	lease capital equipment
CAH	contract another hospital
CMO	contract mobile operator
h_1	current operating hours per day
h_2	new operating hours per day for UES option
d_1	current scheduled days of operation
d_2	newly scheduled days of operation for UES option
c_1	current cost per MRI exam
c_2	new cost per case for UES option
Q	target annual number of exams
q_1	current MRI exams
q_2	additional MRI exams
p_1	current operating personnel
p_2	additional operating personnel for UES option
ct_1	current number of CAT scans
hr_1	current operating hours for CAT
hr_2	additional operating hours for CAT option
ct	total number of CAT scans
cs	estimated cost of a cat scan
tc	total cost for CAT exam
Q_B	current number of MRI at Hospital B
bc	cost per MRI exam for region B
ac	incremental cost
fe	fixed number of exams by private operator
fp	fixed price by private operator
lc	monthly lease cost
g	geometric gradient
i	discount rate

CHAPTER 1.0
INTRODUCTION

1.1 Background

The Canadian Health Care System is publicly financed, primarily through taxation, health premiums, and other special payments. Its aim is to provide all Canadians with health care coverage by adhering to five principles: 1) accessibility -- imposing no significant deductibles or co-payment on patients, 2) portability -- recognized by other Provincial coverage, 3) universality -- covering all citizens regardless of race, financial status, and religion, 4) publicly-administered -- under control of a public, non-profit organization, and 5) comprehensiveness -- covering all medically-necessary care [R.S.C, 1985]. Nevertheless, assuring that all necessary medical services are available is becoming extremely difficult, because of increasing fiscal constraints to the health system imposed by federal and provincial governments to lessen significant budget overruns and accumulated deficits [CAC, 1996].

1.2 Current Health Care State in Canada

Health care in Canada is undergoing rapid changes. Each year, hospitals are faced with the demand to reduce operating and capital budgets. The most significant factor influencing reduction to hospital funding is government restructuring at both the federal and provincial levels. Restructuring is a means for debt reduction at both levels of government. Education and especially health care are the hardest hit by government cutbacks. In provinces such as Alberta and Ontario, government is employing drastic measures to reduce existing funding to hospitals. This has resulted in closing some care facilities, while others have been downsized from a referral facility to a community care centre. In some instances, hospitals have consolidated services at one central location. With the magnitude of changes taking place in health care, it is unclear what long-term effects are going to develop. Although, one thing is for certain, there appears to be a widespread consensus that cuts to health care funding are far too sudden and severe. This consensus is documented by growing wait lists for operative services, such as hip and

knee replacements [CAC, 1996]. Non-operative wait lists, such as those for MRI exams are also steadily rising. In fact, patients on MRI wait lists are having to wait approximately six months to receive their MRI examination, whereas patients in other health regions are expected to wait half as long. To avoid excessive wait periods, patients requiring an MRI exam are sent to a nearby health region experiencing much shorter wait lists, which can be anywhere between two to three months [Johnsrude, 1997; Pedersen, 1997] .

Drastic cuts to funding affect hospital operating and capital budgets. Capital budgets are especially vulnerable to reductions with consequent restrictions in fulfilling their capital equipment needs. Hospitals identify the following causes of clinical equipment replacement: obsolescence, deterioration, increased downtime, and rising maintenance costs. Furthermore, rapid growth in technology contributes to major increases in hospital capital costs [Eastaugh, 1981]. It is usually impossible to satisfy all demands for capital funds. Reduced hospital funding can lead to a reduction in the level of services provided to patients. For instance, it is very likely that patient throughput and quality of services is adversely affected when a hospital's emergency department cannot replace essential aging clinical equipment. Much of the equipment used in hospitals is highly technical and complex, and requires special care and maintenance. Not surprisingly, the cost of components for this type of equipment increases with age. Also, major repairs rise, reliability decreases, and operating efficiency declines.

Hospitals competing for scarce capital resources must be prepared to perform a "thorough analysis of new prospective capital investment from a financial and medical perspective." Equally important is a need to incorporate a formal assessment of potential risks associated with the investment [Gapenski, 1992]. It was pointed out by Park (1993) that financial analysis is only one aspect of the decision-making process. Critical to capital budgeting is the need to consider political and strategic issues in addition to economic factors. As capital budgets diminish, there must be greater reliance placed on developing,

and consistently using, a comprehensive evaluative process with objective analysis to better analyze and to help prioritize new capital investments.

It is clear that the hospital capital budgeting process must undergo some form of change in order to improve objectivity and effectiveness when evaluating and prioritizing proposed capital investments. It is no longer sufficient for hospital managers to submit capital requisitions without formally documenting the evaluation and prioritizing processes used to derive the requests. Furthermore, supplying information to decision-makers describing the characteristics and usefulness of existing equipment is important, especially if it can be used in some capacity elsewhere in the system. Also, all capital requests involving a significant capital outlay (say, $50,000 or more), need to define the financial and operational implications to other subsystems which may arise from implementation of the proposed capital investment.

1.3 Statement of the Problem

Severe reductions to operating and capital funding have placed a tremendous burden on hospital operating systems. More specifically, hospitals are not able to replace aging capital assets resulting in problems which include: higher operating costs, increases to wait lists, increased downtime, decreased throughput, and significant reduction in operating efficiency. The combined effect from these problems together with resource constraints create unstable conditions which greatly affect hospital-wide system performances. Furthermore, patient access and the quality of delivered health services are certain to suffer under these conditions.

The current methodology used by hospitals in evaluating capital investments and system performances are inadequate. Decision makers are supplied with information derived mostly from subjective analysis; and as a result, they cannot arrive at informed decisions because of biases deep-seated within the current capital budgeting process. There is insufficient objectivity in the evaluation process, and it appears that most decisions are made for intuitive or "political" reasons. Furthermore, there is no thorough assessment of

risk provided in the current methodology. Another area of concern in the capital budgeting process deals with insufficient coordination and collection of both operating and cost data. Canadian Hospitals need to adopt systems that ensure better public accountability. Without measures of accountability, the public will lose confidence in the health care system. It is expected that overall expenditures will continue to rise, unless health care reform includes a greater component of analytical cost control and public accountability. Hospitals must carefully adopt and implement decision strategies, only after management has fully explored alternative design options geared towards solving problems dealing with critical issues (one example is wait lists for knee and hip replacement procedures).

Unfortunately, within the current political and economic climate, hospitals are not prepared with tools to rigorously analyze and deal with potential future cost-cutting problems. It is very evident from the capital budgeting decision-making process currently used by hospitals that managers need to be better and sufficiently equipped with a set of analytical tools which permit an objective analysis of both existing and future cost-cutting problems [Watts et. al, 1993]. There is no systematic and comprehensive methodology for approving capital budgets. For instance, in the past, some hospitals have relied on the information supplied from a one-page check-list type worksheet, similar to the one used by Hospital A shown in Appendix I for capital requests, where department managers are required to check appropriate boxes pertaining to the request. A section in the middle of the worksheet is provided for justification of the capital request. The worksheet does not explicitly request an assessment of a detailed cost structure to identify which cost drivers are likely to be impacted by the proposed capital investment, nor is there any request for information regarding cost implications to other subsystems. This is just one of many similar examples of a non-structured approach to hospital capital budgeting.

In short, it can be seen that without a formal evaluation process, capital requests continue to be administered on an ad-hoc basis with decision-makers obtaining, on a regular basis, an incomplete information package related to recommended capital investments.

1.4 Rationale For Appropriate Evaluation Tools in Hospital Capital Budgeting

Many capital expenditure requests are made to replace worn and outdated equipment. Advancement in technology renders much clinical equipment obsolete. Without timely replacement, or upgrading, it is very likely that hospital productivity will decline with an accompanying increase in operating cost per patient. However, A fundamental principle in economics states that resources are finite in nature. Capital funds are not only finite, but more restricted as a result of cost-cutting initiatives exercised by the government in its attempt to reduce the provincial debt level. Inevitably, all hospitals within their respective health regions must compete for the same capital funds. Obviously, the larger tertiary centres offering specialized services will be bidding for a relatively larger share of total available capital. Although the tertiary referral centres have some influential power over the smaller community care centres, they are not guaranteed full funding of proposed capital investments. The provincial capital fund is accessible to all health care centres. In other words, every health centre must compete against one another. The underlying message is that all health care centres are required to demonstrate need.

In some instances, as the demand for certain services grow, so does the need for increased capital equipment. For instance, seniors may require more frequent joint replacements. Without adequate capital funding, hospitals may not be in a position to provide the required level of increased services. Again, hospitals must demonstrate the need for additional capital equipment requirements. Simply requesting capital funding does not guarantee its approval. Hospitals must demonstrate the need for capital more convincingly and analytically. This can be accomplished by performing a complete and thorough assessments of their proposals by using functional, sensitivity, and stochastic models. Such assessments will include subjective considerations, but will provide a much greater degree of objective reasoning.

The future and current demand for MRI services together with the political and economical climate in Canada require that a comprehensive, and thorough analysis are carried out to address system performances and the associated capital budgeting problems. An analysis of this caliber must be based on rigorous mathematics and sound economic judgment to ensure efficient system management. In this study, a systematic and comprehensive approach is developed to enhance the MRI performance and current capital budgeting practices. A series of scientific and analytical tools are defined and illustrated, including MRI structural design options, sensitivity and stochastic models. This study provides hospital management with efficient management tools for improving the MRI system operations and economics significantly.

1.5 Research Methodology

This study uses a number of tools and techniques in designing the MRI system performance and economic models. A literature review of past and current capital budgeting practices has identified the need and importance of incorporating some of these tools and techniques. The MRI system performance and capital budgeting problems are modeled using structural design and functional moment methods. Stochastic models of the MRI system are developed to capture the system variability.

Sensitive variables from the functional moment analysis are further processed with Bestfit to produce probability distribution functions (PDF), and are used as inputs in the stochastic models. The Monte Carlo simulation technique is used to provide solutions to the stochastic models to obtain the mean and variance estimates and the associated opportunity costs. The methodological approach used to solve the MRI's capital budgeting and system performance problems are intended to provide more objective information to hospital management.

1.6 Objective of the Study

The objective of this study is to enhance the current hospital capital budgeting process used by Canadian hospitals to evaluate capital investments. The elements of this objective are to i) design technically feasible structural MRI design options to improve the system performances; ii) develop functional, sensitivity, and stochastic models of the health care budgeting process; iii) apply the models to solve the MRI problem in a selected health care system (i.e., Hospital A); iv) validate the MRI models with real world data; v) select an MRI option that minimizes unit cost and improves the quality of delivered services, and 5) provide recommendations regarding the implementation of selected the option in the chosen health care system.

1.7 Scope and Limitation of the Study

This research focuses on applying sophisticated analytical tools and techniques to develop models which are used to solve hospital system performance and capital budgeting problems in Canada. A generalized stochastic capital budgeting model is developed to analyze structural design options of an MRI system. Seven base and 21 variant structural design options are developed to solve the MRI's capital budgeting and system performance problems. Mathematical and computer modeling are carried out to provide solutions to these structural design options. The three stages in the development of the mathematical modeling process include: the functional, sensitivity, and stochastic models. The functional model identifies the elements of the annual equivalent cost (AEC) function, while the sensitivity models employ the functional moment methodology to identify sensitive random variables for each of the seven base options. The sensitive random variables are further processed and fitted with probability distribution functions (PDF) which subsequently serve as inputs to the stochastic models. The Monte Carlo simulation technique is used to provide solutions to the stochastic models of the base and variant design options. These 28 design options are ranked based on their ability to minimize cost and maximize system performance.

In this research, the final results from the stochastic capital budgeting model are restricted only by the availability of accurate input data. Data gathering proved to be a formidable task, because hospital management and other sources were reluctant to share financial and operating data. Furthermore, private operators of MRI systems were even more resistive to sharing information. Other factors influencing the limitation of the stochastic capital budgeting model include fluctuating rates associated with labor and supplies, cost of borrowing, capital assets, and inflation. In addition, the data had several entries which involved accruals of expenditures. This particular practice resulted in large variabilities among random variables. Data which could not be readily collected was estimated through discussions with suppliers and relevant companies.

1.8 Contribution to Knowledge and Industrial Significance

The contribution to knowledge of this research can be summarized as follows:

i) This research charts a new direction with the combination of the functional moment and stochastic modeling techniques for an MRI system performance and cost modeling. This is the first time these techniques have been used to solve healthcare problems; ii) This study provides a unique direction and focus for efficiently operating the MRI system in this teaching hospital, the corresponding Capital Health Region, the province of Alberta, and in Canada; iii) This study also provides hospital management with new and effective management tools for managing in an uncertain political and economic climate. iv) This study expands the application of computers from word processing and database management to performing simulation studies in a healthcare setting. More specifically, using developed economic models to simulate the MRI system in order to optimize its cost and performance. Results are presented using a graphical interface so the hospital management can interpret results more effectively.

The author develops structural design options to improve the MRI system performance. This study also provides hospital decision-makers with a *systematic and a scientific capital budgeting process* that supports both quantitative and qualitative analyses. Its

aim is to enhance the level of information provided to decision-makers which can be used to guide the development and implementation of strategic policies. Hospital managers can develop strategies for objectively allocating new resources by evaluating the estimated cost structure along with appropriate changes to clinical practice guidelines. For instance, hospital managers, after reviewing the estimated cost per unit of output for hip replacement, knee replacement, and cardiovascular surgery, can strategically decide how many of each to perform, given that only a finite amount of new resources are available for allocation to capital requests. Furthermore, in their decision-making process, they must also consider the impact to other processes, as a result of increasing throughput. For instance, increasing hip replacement surgery has adverse effects on caring for patients requiring physio-therapy, unless the increase in patient volume is communicated effectively to the rehabilitation department well in advance of its actual occurrence. In effect, the goal of the structural design options is to present hospital management with a series of choices from which they can select a technically feasible, and economical design option to solve the MRI's system performance problems. Each option is governed by specific design parameters which are likely to be influenced by the dynamics of the existing political and economic climate. Thus, hospital management must consider a broad range of healthcare, financial, and economical issues when evaluating the list of MRI design options. In other words, these MRI design options forces management to look beyond the "bottom line".

Significant emphasis is placed on transfer of technology to permit health care analysts to use advanced analytical tools, such as computer simulation and discounted cashflow modeling, to facilitate an effective objective economic analysis of the proposed expenditures. For example, using Monte Carlo simulation in this study permits decision-makers to observe the effects of risk. Risk is quantified by way of user-specified probability distributions. The advantage of specifying a probability distribution, compared to a point estimate, is that a range of probable outcomes can be clearly defined around which to support decisions.

The stochastic capital budgeting model also provides information regarding the sensitivity of random variables so that the analyst can carefully monitor those variables which significantly contribute to the total variance in the cost function. This is especially important, because any deviation in a random variable from its design constraint can lead to increases in total cost. Identifying sensitive random variables are important, because it results in a reduction in the number of variables for which data must be collected and thus, reduces data gathering cost and time.

The stochastic capital budgeting model identifies and quantifies risk associated with a proposed capital investment. This particular feature of the model enables managers to determine the risk of not being able to meet the objective of the design system (i.e., risk of failure), and also defines the cost structure that accompanies the risk. Conversely, hospital managers are presented with the risk of attaining the design system's objectives (i.e., risk of success), and it is also accompanied by the appropriate cost structure. With information surrounding risk, hospital managers must decide what levels of risk to accept in order to attain the design system's objectives. In addition, an audit trail can be established by comparing the proposed cost information from the stochastic model with those obtained from the actual operation, once the new changes have been introduced into the subsystem. Managers can use this information to help determine if performance target levels are being met as set in the design option. Performing an audit is important, because deficiencies can be identified early in a process. As a result, corrective measures can be initiated to minimize cost overruns.

1.9 Structure of Study

Chapter 2.0 deals with a comprehensive literature review of the theory and current practices used in capital budgeting. The literature review compares capital budgeting in the health care industry to other sectors, such as an industrial setting. Also, specific aspects of analytical tools are discussed to heighten the awareness of their application in a capital budgeting environment. In fact, it is shown that some analytical tools are preferred over others. Chapter 3.0 fully develops the mathematical models used in this

research study. The mathematical modeling is carried out in three stages to create functional, sensitivity, and stochastic models. The functional model describes the variables used in defining the annual equivalent cost (AEC) function, while the sensitivity model produces a variance component analysis which identifies random variables which are likely to impact the AEC function. A stochastic model is constructed to provide a numerical solution from the derived mathematical expressions, which is achieved by incorporating a Monte Carlo simulation technique. Simulated results are used to estimate an expected AEC, as well as, quantifying its probable outcome.

The design options used in solving Hospital A's MRI system's performance problems are described in Chapter 4.0. Seven base design options are being considered where each base option is associated with three variant options. Altogether, there are seven base options and 21 variant design options. Each options is intended to address and provide a solution to resolve the problems surrounding Hospital A's MRI subsystem. Some of these problems include: growing wait list, reduced operating efficiency, and increased maintenance cost to name a few. Computer modeling and experimental analysis are discussed in Chapter 5.0. Computer modeling entails a detail discussion of the algorithms used to solve the complex set of mathematical expression derived in the sensitivity and stochastic models. Essentially, computer modeling provides a medium through which a numerical solution can be achieved from these mathematical expressions. The experimental aspect of this research involves a discussion of the design options matrix, the required data for validation, the number of iterations in a simulation run, and the experimental setup and experimentation.

A thorough discussion of the results from the sensitivity and stochastic models are presented in Chapter 6.0. More specifically, issues and strategies are developed to resolve the problem associated with Hospital A's Magnetic Resonance Imaging (MRI) system. The results from the seven bases and 21 variant design options are presented to provide solutions to combat Hospital A's MRI system problems. These problems include: lengthy wait list for MRI exams, increase in demand for MRI services, fiscal constraints

on the system, improvement in productivity, maximizing equipment utilization, identifying risk, quantifying opportunity cost gained or lost, and identifying sensitive cost variables relative to the AEC function.

CHAPTER 2.0
LITERATURE REVIEW

In this chapter, an extensive literature review is carried out by evaluating past and current capital budgeting practices. Also, broad coverage of relevant issues is provided, including analytical techniques used in capital budgeting analysis, operational issues when evaluating capital acquisitions, and cost accounting issues.

2.1 Definition of Capital Budgeting

Capital budgeting is defined as a "perennial multidisciplinary function involving engineering, finance, and management. It addresses the question as to the size of budget, assets to be included, and the mode of financing" [Gurnani, 1985]. In essence, capital budgeting is really about departments working together to create a plan to guide capital purchases, and to provide a basis for identifying variances from that plan.

2.2 Current State-of-the-Art Methods For Evaluating Hospital Capital Budgets

Years ago, Canadian hospitals did not face the problem of equipment replacement, because resources were plentiful. In fact, hospital managers could be assured that they would receive capital funding similar to the previous period, adjusted by inflation. With this knowledge, departments planned for new capital acquisitions without providing much justification, or presenting a thorough analysis.

Several factors determine if hospital departments are successful in gaining approval for their capital project proposals. The most prominent factor is *politics*. Meyer (1985) states that "individuals, groups or sub-units seek to advance their own interest in amassing power and exercising it to influence outcome". Elements which exercise significant influences on the political decision-making process include: 1) scarce resources, 2) dependency, and 3) conflicting goals [Meyer, 1985].

A number of researchers, with the use of surveys, have explored capital budgeting practices to determine the extent to which state-of-the-art techniques are applied in evaluating capital projects [Kamath and Elmer, 1989; Pike, 1989; Kim et al., 1984].

Kamath and Elmer (1989) discovered that hospital capital project decisions are made on an "as needed" basis. They further note that, historically, hospital capital budgeting practices have lacked quantitative sophistication. The results from their survey indicate that only 26 percent of respondents relied on formal capital budgeting techniques when evaluating new prospective investments in medical equipment. Approximately 66 percent of respondents used the payback period method as the primary capital budgeting tool, while only a small percentage used the time value methods such as net present value, internal-rate-of-return and profitability index [Kamath and Elmer, 1989]. One plausible explanation is offered as to why the payback period is used as a preferred primary tool. It is believed that managers use it as a rule of thumb when "...profitability is not a motivating and crucial factor in the investment decision..." [Kamath and Elmer, 1989].

Pike (1989) uses a survey to examine two issues: (1) the extent to which investment practices have changed over time, and (2) whether sophisticated capital budgeting techniques are perceived by managers to improve the decision-making process. His findings indicate an increase in the use of discounted cashflow and sensitivity analysis techniques over the period in which the survey was conducted (i.e., 1980 and 1986). Furthermore, managers perceived that the increased use of sophisticated capital project techniques enhance the effectiveness of capital budgeting. Pike (1989) credits the encouraging results from his survey to the rapid growth in end-user computing, and the availability of inexpensive financial software.

Kim et al. (1984) compares capital budgeting practices used by U.S. and non-U.S. multinational companies. Their findings indicate that U.S. companies place a higher emphasis on using sophisticated capital budgeting techniques. More specifically, U.S.

companies use internal-rate-of-return and net present value techniques, because these methods recognize the time value of money. Again, the results from this survey are encouraging and consistent with those obtained by Kim et al. (1989). Thus, U.S. companies appear to recognize the importance and value of using sophisticated capital budgeting techniques to provide management with more object information surrounding potential investment projects.

In summary, companies using state-of-the-art sophisticated capital budgeting techniques to evaluate potential investment projects benefit from increased objectivity in the decision-making process. Decision-makers can make informed decisions by considering both quantitative and qualitative information presented to them. Hospital managers can also realize substancial gains from using these sophisticated capital budgeting techniques. Eliminating biases associated with current subjective hospital capital budgeting practices and using modern evaluation techniques can "...promote independent evaluations" [Meyer, 1985].

2.3 Capital Budgeting In Health care

Health care literature does not prescribe any specific methodology for evaluating capital projects. Some articles devote much of their attention to looking at only one aspect of capital project analysis -- sensitivity analysis which enables decision-makers to observe one probable outcome at a time. Other types of literature focus on specific treatment of input parameters in an investment analysis such as cash flow projections, use of appropriate discount rate, depreciation methods, and treatment of inflation [Riggs et al., 1996].

Kamath and Elmer (1989) indicate that little objectivity is introduced in capital project analysis. In fact, they indicate that most hospitals rely on using simplified financial tools such as payback method to evaluate capital project. As a result, decision-makers are ill-informed with respect to critical information affecting capital projects, such as risk and uncertainty. Interestingly enough, they are encouraged to see a shift by other hospitals to

collectively use standard discounted cash flow (DCF) techniques, such as net present value (NPV) and return on investment (ROI). They discovered that only 30 percent of responding hospitals claim to have "explicitly" considered risk in their analysis.

In contrast to a survey of non-hospital organizations, they note that risk-adjusted discount rate and shortened payback period appear to be the two most commonly used methods for providing "built-in" contingencies for risk. Only about five percent of the respondents claim to have used simulation modeling to assess risk. In fact, a common approach used by managers in assessing risk in capital project evaluation is to rely on past projects with similar characteristics or profiles.

Thus, it is clear that hospital decision-makers are not receiving a sufficiently-wide range of accurate information to determine the economic feasibility of an investment. The methods currently used in capital project analysis fall short of providing adequate information and insight. In periods of capital rationing, decisions surrounding capital projects favor hospital managers who are able to demonstrate need by presenting an investment analysis that includes the highest degree of objectivity.

Gapenski (1992) states that hospital managers must perform a thorough analysis of proposed capital projects from a financial and medical perspective. He emphasizes that a capital project analysis must include an assessment of potential risk and anticipated returns. His observation of current practices used in assessing risk indicates that most hospital managers place little emphasis on capital risk. In other industries, risk analysis is an integral component of the capital project analysis.

Gapenski uses Monte Carlo simulation to perform risk analysis, because it captures a more complete analysis of probable outcomes associated with an investment. An advantage to using simulation is that hospital managers can observe a range of different scenarios by varying more than one parameter in the analysis. Gapenski is effective in illustrating the impact of risk assessment on capital project analysis by using a

mathematical tool -- Monte Carlo simulation. However, he cautions that input parameters to any simulation model must be carefully scrutinized, otherwise the simulation can yield erroneous results.

Nichols' (1994) details the importance of using sophisticated tools to evaluate pharmaceutical investments with high levels of inherent risk, uncertainty, and complexity. It can take years for a drug to reach the market place, even then, its success is speculative. Large sums of money are invested with the hope of a successful introduction, and a healthy rate-of-return on investment. Thus, using a scientific approach to analyzing financial investments is a critical step in clearly identifying measures of profitability and risk. Lewent (1994) notes that "...sometimes traditional analysis that factors in time value of money may not fully capture strategic value of an investment, because cash flows are severely discounted when analyzed over a long time frame. As a result, volatility and risk are not properly taken into account."

In most instances, Lewent (1994) states that Monte Carlo simulation can be used to overcome deficiencies present in other methods, because "...it represents a sophisticated mathematical analysis useful to evaluate economic factors such as pricing, inflation, and selling costs". In summary, this article illustrates the importance of introducing objectivity into an investment analysis. Equally important, it also demonstrates the versatility and strength of the Monte Carlo simulation's applicability to diverse environments, such as the pharmaceutical industry, where risk analysis is a necessity.

Meyer (1985) states that capital budgeting decisions are driven by forces moving in opposite directions. For instance, physicians tend to be major lobbyists for capital projects that serve to advance their personal interest. Initially, a large number of capital project requests originate from physicians. No formal evaluation accompanies their request. Rather, they vehemently argue that an investment is needed to improve medical intervention, thus leading to improving quality of life. In other words, it is unreasonable

to place costs above preservation of life. It is a fact, however, that these types of arguments are no longer sufficient.

Meyer adds that a rationale must accompany capital project decisions to overcome rampant bureaucracies and political biases. In short, capital budgeting in hospitals is effective only if the information used by decision-makers is filtered to remove undesired biases, and includes a higher degree of rationale.

There have been several approaches initiated by hospitals in formulating a systematic capital budgeting process. For example, Horizon Health care System -- a four-hospital not-for-profit health care system uses a worksheet survey methodology for evaluating capital projects. Administration's main concern when analyzing capital equipment requests is a demonstrated need within the system and the community.

A series of capital project guidelines accompanied by a Capital Investment Decision Evaluation Worksheet developed by Horizon Health System is used by administrators to assess the overall impact of equipment as it relates to: 1) an organization's mission/vision, 2) market position, 3) quality of service, 4) medical staff , and 5) financial implications. Appendix II includes a sample of the worksheet used by Horizon Health System. The level of detail in the analysis for each capital project proposal is a function of scope and varying size. For instance, proposals exceeding $1M dollars require extensive analysis, while those less than or equal to $500,000 require only a narrative review. A narrative review is carried out by addressing topics presented in the developed worksheet. Hospital administrators considered assigning point values to answers found in the evaluation worksheet; however, devising an appropriate point system presented difficulties.

Wideman (1992) describes a capital budgeting system that uses a point rating system, as a decision tool to determine the feasibility of an investment costing over $4M. This system is used by the Daughters of Charity National Health System (DOCHS) -- a health system

that oversees 60 health care facilities located in 33 U.S. cities with more than 16,000 beds.

The overall objective for using a rating system is to demonstrate need. One of the benefits arising from using a rating system is to provide decision-makers with a "succinct statement of the risk involved." DOCHS draws a parallel from the rating system used by Standard & Poor and Moody's, where information of credit worthiness is gathered about an organization. The message being conveyed is that a rating system provides a "wealth of analysis and information." The rating system was adopted in 1988 in order to quantify risk associated with business and financial matters relating to community needs and investments in a wide array of projects.

2.4 Capital Budgeting Steps Used By Hospitals

A hospital prepares its capital budget separate from its operating budget. However, it should be noted that activities and strategic planning surrounding the capital budgeting process are closely linked to the operating budget [Nestman, 1989]. In some instances, hospital departments must make adjustments to their operating budget to reflect changes arising from newly-acquired equipment. For example, additional training might be involved for staff and maintenance personnel.

A typical hospital capital budgeting process consists of four steps [Watts et al., 1993; Nestman, 1989]. These steps include:

- Capital requests are prepared and submitted by each department.
- Submitted requests are reviewed and assessed; these steps can be politically biased, especially when limited information is available.
- A final list is developed and prioritized by some method of ranking proposals which, for the most part, is not clear.
- The final step occurs when the capital budget is submitted for approval to the hospital's Board of Directors.

A hospital's capital budgeting process does have its own particular flaws. For example, Watts et al. (1993) identify two important limitations to a hospital's capital budgeting process. First, there is inadequate monitoring of utilization and effectiveness of existing capital equipment. Second, there is limited expertise among members of the capital budgeting committee. As a result, they are unable to contribute to issues relevant to newly-proposed capital equipment [Watts et al., 1993].

Inadequate monitoring, utilization and effectiveness of existing equipment by hospital departments lead to poorly collected information. Watts et al. (1993) noted that information supplied by hospital departments regarding existing equipment was "too sketchy." In other words, decision-makers could not draw any conclusions about the current state of the equipment ear marked for replacement. For example, decision-makers could not infer whether the existing equipment could be used, and if so, for what length of time, and at what cost?

It is critical that capital budgeting committee members be knowledgeable of the underlying issues and consequences surrounding a prospective investment. Otherwise, operational issues and technology implications can easily be overlooked in the decision-making process. Issues that warrant concerns include: safety, maintenance contracts, worker training, equipment compatibility, and future enhancements.

2.5 Capital Budgeting In Industrial Organizations

An overall assessment of capital budgeting in non-health care organizations is provided by Gurnani (1985). The purpose of reviewing Gurnani's article is to contrast his analysis of survey findings to those observed by Klamath et al. (1989) survey of hospital capital budgeting practices. Gurnani (1985) discovered that the time value of money is thoroughly understood capital-intensive industries.

Companies is such industries as petroleum, mining, chemicals, communications, power and national gas distribution rely on discounting cash flows as either the exclusive, or the

most important, economic evaluation procedure. Managers, engineers and accountants these firms are expected to routinely use sophisticated capital investment analysis techniques and project management. Surprisingly, the percentage of projects that are justified by taking the time value of money into account is still low. Interestingly enough, some companies avoid using economic evaluation when projects are deemed "mandatory". A smaller proportion of companies as compared to hospitals, use payback period as a primary criterion for evaluating capital projects. In summary, although most non-health care companies understand the concept of discounting, "...the rate of adoption has been rather slow..." in using widely-accepted sophisticated tools to perform economic evaluation of capital projects. Thus, it is apparent that most hospitals and many non-health care organizations do not apply sophisticated techniques to their capital project analyses.

There are some distinct differences when comparing capital budgeting processes between hospitals and for-profit organizations. From a management accounting perspective, Anthony and Young (1994) noted that for-profit management must carefully prepare capital budgets for two reasons -- cost structure and spending flexibility. In for-profit companies, especially those in manufacturing, future costs can be estimated within reasonable limits, because operations must adhere closely to design and engineering specifications. In comparison to hospitals, however, capital costs during a period can vary widely depending on management's decisions, and many can be categorized as discretionary.

Hospitals do not have as much spending flexibility. They tend to exhibit stable and predictable spending patterns. There are seasonal variations in patient volume, of course, but with the aid of historical data such variations can easily be reflected in the capital budget. For-profit companies allow for flexibility in their capital budget in order to accommodate changes arising from relatively sudden changes in cash flow, new investment opportunities, and unpredictable events which can occur at anytime.

2.6 Capital Budgeting Steps Used By Industrial Organizations

The stages of a capital budgeting process which a for-profit company might follow, once a *potential* capital project is identified includes: (1) defining the capital project and predicting the outcomes from its purchase, (2) performing a detailed analysis of the capital project using financial techniques such as net present value, internal rate-of-return, payback, accrual accounting rate-of-return, urgency, (3) identifying financing sources for the capital investment (i.e., internally, equity-security capital markets, debt-security capital markets), and (4) implementing the capital project, and monitoring performance. It is often useful to document the project's justification, progress and results to help provide guidance for future documents.

It is clear the capital budgeting process outlined above places a great emphasis on quantitative techniques. Rightfully so, because a poorly-evaluated investment can have adverse effects on operations. More specifically, it can reduce net positive cash flows which for-profit companies rely on to meet objectives. Mistakes in capital projects can lead to insolvency, because capital equipment can represent a very significant negative cash flow.

Of course, not-for-profit hospitals in Canada need not worry about insolvency. Because hospital operations are publicly-funded, a poor investment does not result in closure. Often political tactics are exercised by hospitals to solicit additional funding from the government health agency to mitigate deficits. Sometimes, however, only part of the deficit is funded. For-profit companies are not afforded such an option. They must finance their needs by using retained earnings (if any), selling a portion of ownership of the company (stock), or borrowing by selling bonds or obtaining a loan from a bank or other lending institution.

Thus, capital budgeting plays an important role when evaluating capital projects. It is evident that a more objective approach is taken by for-profit organizations when performing investment analysis. Hospitals cannot ignore the benefits arising from using

techniques such as Net Present Value analyses. Incorporating formal evaluative analysis can provide practical advantages, especially when hospitals must compete against each other for scarce capital resources.

2.7 Techniques Used In Evaluating Capital Projects

Financial planners have always been criticized for not using sophisticated techniques in evaluating capital projects. Kamath and Elmer (1989) suggest that "capital budgeting techniques used should facilitate evaluation of any project in terms of its ability to increase its net cash flows in the long run and reduce the risk associated with a hospital's cash flows." As well, these techniques can be used to assist in evaluating a project's contribution to market share, meeting community needs, and increasing the probability of survival. A discussion of commonly-used techniques in capital budgeting is presented to gain an appreciation of the level of sophistication among the different types of techniques.

2.7.1 Project Profitability Criteria

In capital budgeting decisions, the Discounted Cash Flow (DCF) method is used extensively, because it takes into account the time value of money. It is usually one of the better methods available for use in long-term decision planning. There are two main variations of the DCF method which are the Net Present Value (NPV) and Return-on-investment (ROI). To determine NPV, a minimum acceptable ROI must be specified. It is sometimes called internal-rate-of-return (IRR), cost of capital, cut-off rate, social discount rate, or hurdle rate. These two main variations are referred to as DCF NPV and DCF ROI.

The DCF NPV remains the most understandable method for evaluating and comparing capital projects, because it stresses net profitability above (or below) a required minimum. However, it does not account for differences caused by the size of projects. There are two assumptions involved in using the NPV method. First, it assumes a world of certainty. That is, risk (discount) rate is constant (and correct) throughout the life of

the investment, and cash-flows will occur in the amounts predicted, and at the times indicated.

Secondly, the original amount of the investment can be viewed as borrowed, or otherwise "available", at the specified minimum rate. Capital projects yielding a positive NPV, are estimated to earn more than the cost of capital. As such, these investments pass through the analysis "screen", and are favorably considered by management. A negative NPV might automatically obviate a management review, or at least present a strong argument for rejecting a proposed investment.

The ROI (or IRR) method is similar to the Profitability Index (PI) method, because they are both measures of profitability. The ROI/IRR is defined when NPV is equal to zero. The resulting ROI/IRR can be compared against the company's Minimum Acceptable Rate-of-Return (MARR) that it receives from its pool of investments. An ROI/IRR which is less than MARR results in the rejection of a proposed investment, unless strong reasons exist to modify such a decision. Determining a project's ROI/IRR is an iterative process which can be easily solved using financial calculator or a spreadsheet. It is a popular method, because it is relatively simple, mathematically, and seems to be logical and objective. Non-financial managers can learn enough about it to believe its results.

The break-even analysis method enables managers to estimate the level of operation at which point economical feasibility is lost or achieved. For example, managers might want to determine how far the level of throughput would have to fall before an operation provides an adequate ROI/IRR. They can determine *a point* in the operation which results in a NPV=0. This particular point is called the *break-even point*. The break-even point can be set using any rate-of-return; however, it is preferred that the rate used is the organization's MARR. When profitability surpasses the break-even point, a positive NPV is achieved indicating adequate profitability (or an acceptable ROI/IRR). In other words, as long as volumes maintain adequate net positive cash flows, the operation will have a positive NPV. Otherwise, if volume decreases below the break-even point and

negative cash flows (i.e., capital expenditure) do not decrease sufficiently, operating costs (the other major negative cash flow component) would have to be cut to maintain adequate profitability.

The Payback Period (PP) method looks at how many years are required to recover the original investment. A short payback period implies a desirable investment. Unfortunately, the payback period falls short of explaining the time value of cash flows. It ignores cash flows after the payback period, and fails to use time value justifications to reflect risk. Not surprisingly, it tends to discriminate against slowly-maturing, lower risk projects. The main focus of the payback period is on liquidity. At best, payback is simple enough to be used as a screening tool for capital projects.

The Profitability Index (PI) method is similar to the benefit-cost ratio (BCR) method. An index greater than 1.0 implies that the benefits outweighs generated costs. Thus, the capital project would be acceptable in terms of profitability. It is worthwhile to note that PI provides a measure of relative (i.e., relative to the initial capital) profitability.

The Accounting Rate-Of-Return method permits the analyst to convey a "crude" measure of profitability as defined by the ratio of net annual profits to the investment outlay. Using this measure does not reflect aspects pertaining to time value of money, nor does it provide an indication of the amount of risk associated with an investment.

2.7.2 Sensitivity Analysis

Sensitivity analyses illustrate the effect of varying input variables which are considered uncertain, and observing their effect on the operation's profitability using ROI/IRR criteria. Each variable exhibiting uncertainty is varied above and below some expected value. One might think of these variations in expected value as an "optimistic" and "pessimistic" estimates. For example, with respect to a hospital MRI operation, uncertain variables can be volume, market share, unit variable operating cost or, perhaps, salvage value. Intuitively, it is expected that varying volume, and unit variable operating cost can

directly affect profitability, because cash flow is sensitive to changes in these two variables. However, if market share decreases due to an increase in competition from private clinics, then it can be seen that such an action can also adversely impact cash flow.

One potential flaw which exists with the sensitivity method is that results obtained may be ambiguous. For example, it is necessary to have all information coordinated and collected from affected departments in order to arrive at optimistic and pessimistic estimates. Otherwise, estimates can be misinterpreted when examined by managers. Another potential problem is that some of the stochastic variables are likely to be correlated with each other. For example, optimistic estimates in unit prices may be understated, especially if inflation pushes prices above estimates. The result is that costs are also likely to be inflated.

2.8 Elements of Cost Modeling

Inflation is defined as a persistent rise in the general price level, usually resulting in the decline of purchasing power [Chan, 1993; Riggs et al., 1996]. Consistent treatment of inflation is critical to an economic investment analysis. In other words, cashflow and the discount rate must be either nominal or real in terms, but not a combination of the two. For instance, the analyst cannot apply an inflation-adjusted discount rate to nominal or constant cashflow. If inflation is considered in the investment analysis, then both cash flow and the organization's minimum acceptable rate-of-return must be adjusted for inflation.

There can be several causes of inflation which would affect an engineering economic study. For instance, these causes include an increase in the supply of money that fuels relative increases in expenditures for the same goods when consumer demand exceeds supply. Other causes leading to an inflationary economy include producers of goods and services passing-on to consumers increasing labor costs which are not matched by productivity gains. On the other hand, consumers are partly responsible for rising

inflation through increased spending patterns. Also, specific events can trigger a general rise in prices in certain sectors. For instance, the energy resource sector charges higher prices when OPEC restricts oil production. For example, the Gulf War in 1991 triggered increases in gasoline prices.

Some consequences of inflation include rise in petty crime, greater unemployment, distortion of the decision-making process, decline in an organization's ability to compete in foreign markets, and increased taxes [Brealy et al., 1986; Riggs et al., 1996; Anthony and Young, 1994]. It is critical for decision-makers to be fully aware of these consequences, when planning and scheduling strategic issues to minimize cost-of-service, and strive to improve both quality and delivery of health care services, which are essential requirements for survival in the twenty-first century [Drucker, 1992]. Inflation can be controlled by tightening the supply of money (often through imposing higher interest rates), restricting credit, and increasing the supply of goods by achieving greater labor productivity [Parkin and Bade, 1991; Riggs et al., 1996]. Other politically-structured guidelines exist to combat inflation, and can be referenced from government annual publications [Brealy et al., 1986].

The literature regarding depreciation of capital equipment from a management accounting perspective is fairly consistent [Granof and Bell, 1991; Anthony and Young, 1994]. Depreciation in accordance with generally accepted accounting principles (GAPP) is defined as the process of allocating (in a systematic and rational manner) the initial costs of plant and equipment, less residual value, if any, over the expected useful life of the asset [Granof and Bell, 1991]. The original cost of an asset, less its accumulated depreciation, is referred to as the *book value* of the asset, and this does not necessarily represent the market value of the asset. In most cases, the book value in each year of the asset's life will not necessarily coincide with the market value for the asset, especially if depressed economic conditions exist in the market place.

Companies are permitted by tax laws, to select a depreciation method which best serves their needs. Some accountants believe that depreciation charges should be allocated based on an asset's efficiency and productivity. It is widely accepted that both efficiency and productivity decline with the increasing age of equipment. Even more important is equipment obsolescence, an accelerated decline in the function of an asset independent of its physical condition. This factor is commonly associated with high-tech equipment. In such instances, the depreciation period needs to be shortened.

The three widely-used methods of depreciating an asset are (1) straight-line, (2) declining balance, and (3) sum-of-the-years-digits. Straight-line (SL) depreciation involves depreciating an asset the same amount each year of the asset's life. This method is the most widely-used in depreciating capital equipment in a health care accounting system. Unfortunately, it does not adequately reflect obsolescence in high-tech medical equipment, and in most instances does not provide a realistic depreciation value [Granof and Bell, 1991; Anthony and Young, 1994]. Sum-of-the-years-digits (SYD) allows expensing a declining fraction of an asset's net depreciable cost each year. The denominator remains constant in the equation, whereas the numerator is the highest in the first year, and then declines each following year [Granof and Bell, 1991; Anthony and Young, 1994]. Declining balance (DB) applies a fixed fraction of the initial book balance each year [Chan, 1993]. For example, when a double-declining balance (DDB) rate is used, the rate is twice that of the straight-line depreciation rate. Obviously, this is the most effective means of matching the book value and market values of a rapidly obsolescing asset, as long as tax laws or inadequate earnings do not preclude its use. SYD is almost always an acceptable alternative.

The DB and SYD methods are referred to as accelerated depreciation methods. Typically, accelerated depreciation is applied to any capital equipment which undergoes steady changes in technology, such as computerized medical equipment. There is no prescribed rule to depreciating capital assets, as long as the costs are allocated in a *systematic and rational manner* [Granof and Bell, 1991]. In this study, the declining

balance is considered to be the most appropriate method for expensing the cost of the MRI, because of its high rate of obsolescence, and relatively low market value after a few years of service.

2.9 Financing Instruments

Canadian hospitals are restricted to the types of financing instruments available for capital acquisitions in medical equipment [Nestman, 1989]. Hospitals must rely on internal funds. Funds can be withdrawn from investments in securities or bonds. An increasing trend is for Canadian hospitals to focus their efforts at raising money through lotteries, or soliciting donations from corporate organizations and private citizens. For-profit organizations often use retained earnings for investment purposes, or they sell equity to new or present shareholders.

Hospitals are not permitted to approach lending institutions to seek capital. Given inadequate capital, they might divert operating (expenses) funds to finance capital purchases. In effect, Canadian hospitals are not expected to operate in a business-like manner. Private hospitals in the United States are able to issue bonds, because they operate on a for-profit basis. They are able to achieve debt financing at a lower rate when compared to equity financing, because creditors are first in-line to stake claim to hospital assets.

Leasing provides an alternative method for financing capital equipment needs. "In 1989 alone, nearly $10 billion of medical equipment, or 25 percent of all medical equipment investment in the United States, was leased rather than purchased. Further, it is estimated that leasing will account for as much as 40 percent of all medical equipment acquisitions within five years [Estaugh, 1981]". There are two types of leases, financial and operating [Sprague and Whittaker, 1986]. The choice of lease depends on the hospital's strategic goals for delivery of health services. For instance, a hospital can select an operating lease to meet short-term demand for certain services, rather than purchasing capital equipment outright which could potentially sit idle as demand decreases. Again, it is important to

note that most hospitals have their operating budget fixed for the current fiscal year. Any additional funding required for leasing capital equipment, as a result of major breakdowns, would have to come from contingency funds. Unfortunately, these contingency funds are limited in quantity, and cannot be expected to satisfy all emergency fund requests. Only departments with acute caseloads are likely to be favored in emergent situations, when critical capital equipment fails to perform at adequate levels.

A financial lease involves an agreement whereby the lessee is required to remit a series of payments over a specified period (usually five or more years) or over the life of the asset. The terms for the lease are specified under a contractual agreement between the lessee and the lessor. At the end of the lease contract, the lessor is expected to recover the full price of the asset (including interest charges). An operating lease is similar to a financial lease in that both types require remittance of equal payments over a specified time period. However, there are two major differences when comparing an operating lease to a financial lease. Firstly, the duration of an operating lease is much shorter than the equipment's useful life. Secondly, the lessee can opt out of the lease using a cancellation clause written in the contract with the equipment returned to the lessor [Chan, 1993].

Operating leases are most commonly used by hospitals in securing capital equipment, because they transfer risk due to obsolescence from the lessee to the lessor, and the lessee can use the cancellation clause (i.e., when the demand level for some services decreases appreciably) to void the contract. For some hospital departments, leasing is an appealing option when requiring high-tech equipment for only a short period of time. Alternatively, if desired, the option to purchase certainly exists; however, most departments, due to fiscal constraints, would not want to make large capital outlays from their operating budget, especially departments with small budgets.

It is worth noting that several advantages of leasing exist. Gapenski and Langland-Orban (1991) have identified four advantages to leasing capital equipment. These include:

- Leasing preserves cash by providing 100 percent financing. As a result, hospitals can maintain a desired level of cash reserves
- Leased assets are not capitalized, which means that these assets will not appear on the balance sheet. Rather, the monthly payments are accounted for as operating expenses
- Leasing alleviates the burden of financial risk by passing the residual value of risk, including the risk of obsolescence, from hospitals back to the lessor
- Leases based on a per-procedure monthly payment schedule is flexible to allow hospitals to establish new medical services. If the level of service diminishes, hospitals would still be in a comfortable cash position. Whereas, if they purchase new equipment, the financial burden might be unbearable, if equipment sits idle or is underused

Thus, hospitals can pursue leasing as an option to help finance services for short-term demand. However, if it is perceived that a long-term solution is required, then hospital decision-makers must seriously explore capital purchasing, because long-term leasing is not cost effective. Lack of planning for future capital acquisitions would result in a similar situation encountered by the MRI department at Hospital A, where technology has rendered components of the MRI scanner obsolete.

2.10 Risk and Uncertainty

Many capital budgeting decisions involve a measure of uncertainty, and to a larger extent, a high degree of risk. Sometimes, the terms risk and uncertainty are used interchangeably, however, Sprague and Whittaker (1986) make the distinction between the two terms. Uncertainty implies that some relevant information and facts are unknown. For instance, it is difficult to predict the future, and any cost estimate is projected from a combination of historical and available current information. In fact, many decisions are made under a climate of uncertainty, which can create an element of risk [Sprague and Whittaker (1986); Brealy et al., (1986)]. Risk is described as the probability that a venture (investment) has an unfavorable outcome [Palisade, 1996]. In

many instances, this means the venture (investment) might provide an inadequate ROI/IRR, or a negative NPV.

In this research, the capital budgeting decision-making process involves a specific level of uncertainty. Sprague and Whittaker (1986) have identified at least seven causes of uncertainty including: (1) misinterpretation of causative factors that worked in the past, (2) changing external circumstances that invalidate past experience, (3) confronting changes in technology which often results in equipment obsolescence, (4) overstating factors such as revenue, as a result of excessive optimism, (5) conforming to specific conditions without provision for flexibility, (6) changes in government action, such as introducing higher corporate taxes (this can have profound effects on many small businesses), and (7) introducing inconsistent sources of information which lead to errors.

Careful attention must be given to extrapolating historical data into the future, and drawing false conclusions. For instance, reduced interest rate does not always stimulate increased consumer spending, especially where uncertainty exists about the unemployment rate. While historical information is the only available source of data, consideration must be given to the political and economic climate surrounding future decisions.

Changes in technology present a moving target which causes a great deal of uncertainty in cost projections. A Compute Axial Tomography (CAT) scan for a number of years was the leading edge in a radiological exam; however, rapid changes in technology resulted in the development of a much more effective machine known as a Magnetic Resonance Imaging (MRI) scanner. Strategic planning must account for probable and potential changes in technology and budget accordingly.

Government action can also result in uncertainty. For example, the government initiated drastic reductions to hospital funding in order to better align its expenditures with revenue. The result is that many hospital programs are required to adjust the level of

services provided to patients, and in some instances, quality in patient care suffers [CAC, 1996]. It is evident that changes in government policies will continue to cause decision-makers grief, such changes compound uncertainty.

In this study, "quantifying risk" means determining a range of probable values by considering random variables with specific uncertainty. There is no single tool available to accurately quantify risk. Simplistic techniques make strong assumptions far removed from reality, whereas comprehensive methods are difficult to implement. In fact, a combination of subjective and quantitative information is most appropriate for making informed decisions. Seldom is it possible to rely solely on factual data, because there are many unquantifiable social aspects.

Fortunately, use of simulation is one tool which conveniently permits hospital mangers to observe the effects of risk. The stochastic modeling developed in this research makes it possible to determine the probable outcomes of achieving target values. It is important to inform decision-makers of the risks involved when making decisions, because severe cost implications arise from different levels of risk.

Cash flow estimates and economic life are some of the most speculative parameters in any capital investment analysis. Several techniques are prescribed to deal with risk. Allowance for risk can be made by increasing the discount rate, reducing the life of the investment, decreasing the estimate in present value, or reducing the payback [Brealy et al., 1986]. Payback is not usually considered a prime measure of risk. Instead, it is applied extensively to determine if an investment's risk is within an acceptable level.

Other methods of accounting for risk include: certainty equivalent, utility theory, and probabilistic methods (i.e., probability of loss, expectation-variation etc.). All of these methods appear suitable. However, the most likely method is diversification of capital projects as a means to reduce risk and to stabilize revenues.

Selecting an appropriate discount rate to account for risk in a not-for-profit organization is a formidable task. Academic literature suggests using weighted cost of capital which takes into account an organization's capital structure [Sprague and Whittaker, 1986; Brealy et al., 1986]. In other words, both equity and debt are considered in the calculation of weighted cost of capital. Canadian hospitals do not employ debt as is the case with privately-run hospitals in the United States. As a result, it is difficult to estimate this parameter. U.S. hospitals issue bonds to finance investment opportunities and in some instances, fund part of their everyday operations.

Equity is determined by examining returns hospitals experience from using endowment funds to invest in long-term securities and bonds. Unfortunately, these returns have been diminishing, because hospitals are redeeming bonds to fund certain aspects of their operation. There is no longer a large investment base to provide a comfortable return on investment. Currently, the ROI from high-grade debt securities ranges from four to six percent. In short, calculating weighted cost of capital for a hospital presents difficulties arising from an inability to accurately represent the equity and debt components.

Burgess (1981) states that, typically, government-sponsored capital projects, involve the use of a social discount rate which is defined as the "minimum real rate-of-return that a public investment must earn if it is to be worthwhile undertaking. It is intended to reflect the real rate-of-return foregone in the private sector when resources are shifted into the public sector." The Treasury Board (1976) indicated that the appropriate social discount rate for Canada is 10 percent. This rate reflects a weighted average of the pre-tax rate-of-return on displaced private domestic investment, post-tax rate-of-return on domestic savings, and the return required to attract incremental foreign funding. In this research, a 10 percent inflation-free weighted average cost of capital, based on the Burgess (1981) findings, is used to account for risk.

2.11 Simulation Modeling

Hospital capital budgeting literature using simulation modeling is not widely published. Simulation applications in health care are predominantly devoted to evaluating investment proposals pertaining to departments such as surgery, laboratory, and emergency to name a few [Krall, 1995]. Results from these simulations are displayed in a graphical interactive mode. For example, changes to the staffing ratio can be visually observed along with recalculated cycle times for the process in question. However, very little attention is given to applying simulation in capital budgeting processes. Nevertheless, the subject matter is widely addressed in finance, engineering economics, and operation research text books [Brealy, et al., 1986; Park, 1993; Hillier and Lieberman, 1990]. This research uses Monte Carlo simulation to evaluate the stochastic capital budgeting model developed to solve Hospital A's MRI design options. An outline of the technical aspects and application of the Monte Carlo simulation process is presented before, along with a discussion of key elements found in simulation studies.

The use of simulation methodology in hospital capital budgeting is very limited. Klamath and Elmer (1989) points out that less than five percent of hospital respondents from his survey claim to use simulation modeling in their capital budgeting process. One reason for such low acceptance can be attributed to poor availability to simulation software. Ten years ago, simulation software was complex and available only for the mainframe computer. With evolution of the personal computer age, simulation software is much more practical and flexible to use. In this research study, computer simulation plays a significant role in modeling specific design options used to arrive at a solution for Hospital A's MRI problem. Monte Carlo simulation is used in this study, because it provides a more complete picture of a proposed investment [Gapenski, 1992]. Decision-makers are provided with a range of probable outcomes given specific probability distributions for uncertain random variables.

Like many other known tools and techniques, Monte Carlo simulation is only as accurate as its analytical design and input data. No model can transform or manipulate inaccurate

data to reveal useful results. Monte Carlo simulation uses sophisticated mathematics, probability functions and statistics to help transform complex situations into a definable range of outcomes that encapsulate both risk and uncertainty [Niederreiter, 1992]. For this research study, the simulation modeling is carried out by giving careful attention to following elements: formulating the problem, collecting system information and data, representing each source of system randomness by appropriate probability distribution, developing a valid and credible model, and designing and analyzing simulations experiments [Law et al., 1994].

The Monte Carlo method employed in this research represents a significant element of the stochastic simulation modeling process. The usefulness and importance of the Monte Carlo simulation have been demonstrated and applied in different industries to solve real-world problems. Billinton and Li (1994) use Monte Carlo simulation to evaluate reliability of electric power systems, whereas Binder (1986) and Kalos (1982) illustrates its use in solving problems in statistical physics. Niederreiter (1992) points out that natural applications of Monte Carlo simulation arise in problems with a stochastic background, for instance, problems dealing with computational statistics, stochastic optimization, and queuing theory.

The basic procedure of Monte Carlo simulation can be described as a numerical method based on the manipulation of random numbers [Niederreiter, 1992]. However each random number represents a source of potential uncertainty in the final result [Hammersley and Handscomb, 1965]. It is true that Monte Carlo solutions are uncertain, because they are derived from raw observational data which consist of random numbers. Monte Carlo results can serve a useful purpose, however, as long as the uncertainty can be managed so that its contribution remains negligible. Niederreiter (1992) identifies three deficiencies which can further contribute to the uncertainty present in the Monte Carlo simulation. These deficiencies include: (1) the presence of only probabilistic error boundaries, (2) irregularity of the integrand found in its mathematical formulation, and (3) the difficulty in generating random samples. Good experimentation attempts to

ensure that the sample is more, rather than less, representative [Hammersley and Handscomb, 1965].

The simplest method of reducing uncertainty in the final result is to collect more data. Unfortunately, this is seldom an acceptable course of action, because it is labor intensive and not economically feasible (i.e., increases use of computing time) [Hammersley and Handscomb, 1965]. A number of variance reduction techniques have been developed to overcome the uncertainty associated with the Monte simulation process, in order to improve its efficiency. Reducing the sample variance can effectively reduce the standard deviation of the Monte Carlo estimator. The effect of decreasing the sample variance is the same as increasing the number of samples. Some of the variance reduction techniques include: control variates, importance sampling, stratified sampling, and antithetic variates [Hammersley and Handscomb, 1965; Billinton and Li, 1994].

The control variate variance reduction technique relies on information obtained from an analytical model to reduce the sample variance. For instance, if a segment of a problem can be solved by using an analytical model, then the Monte Carlo simulation is employed only to calculate the difference between the solution of the problem, and the analytical segment. The object of the importance sampling technique is to concentrate the distribution of the sample points in the region of the interval which is of most "importance," rather than evenly spreading out the sample points. Stratified sampling is similar to importance sampling, except that a larger number of samples are drawn in the subintervals, which provides the most significant contribution to reducing the variance in the simulation results. Antithetic variates describe any set of estimators which mutually compensate each other's variations.

Another important aspect of the Monte Carlo simulation is random variate generation. A random variate is defined as a random variable which is generated from a given distribution [Billinton and Li, 1994]. It is worth noting that generators of random variates which follow non-uniform distributions are based on uniformly-distributed random

numbers between [0,1] [Billinton and Li, 1994; Niederreiter, 1994]. The procedures used for generating non-uniform random variates include: inverse transform method, composition method, and accept-reject method. In this research, only the inverse transform method is considered; it is the most frequently used method in Monte Carlo simulations. The inverse transform method is used to generate random variates for a triangular and lognormal distributions, and an approximate inverse transform method is used to generate random variates for a normal distribution.

In summary, Monte Carlo simulation plays an important role in this research. The use of Monte Carlo simulation can strengthen hospital capital budgeting analyses by presenting relevant information to decision-makers which has a much more objective basis.

CHAPTER 3.0
MATHEMATICAL MODELING OF A GENERALIZED HOSPITAL CAPITAL BUDGETING PROCESS

The objective of the Hospital Capital Budgeting Process is to design and implement an MRI design option that minimizes the unit cost of an MRI examination in the short and long-term. This option should aim at improving or maintaining the quality of delivered services. An *annual equivalent cost* (AEC) *function* is applied to evaluating capital acquisitions in the healthcare field. The mathematical modeling in this research will be carried out in three stages to create functional, sensitivity, and stochastic models.

3.1 The Capital Budget's Functional Model

The functional model for the AEC depends on many variables as illustrated in equation (1) whose functional form is linear. A brief description for each of the variables identified below is provided in the list of nomenclature.

$$AEC = \phi\left(\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7\right) \qquad (1)$$

The labor cost variable given by γ_1, is a function of the random variables shown in equation (2);

$$\gamma_1 = \phi\,(MedFee, MedSal, RelStaff, PrePay, RegEst, Admin, EmpBen) \qquad (2)$$

The supplies cost variable, γ_2, is a function of a number of random variables illustrated in equation (3);

$$\gamma_2 = \phi\,(Medsurg, ConMed, Drugs, Radiology, Lab, AppSup, Food, Housekpg, Offsupp, GenSupp, Comm, TravExp, ProfFee, EducPrg, PurSrv, ConMain) \qquad (3)$$

The capital cost variable, γ_3, is a function of the random variables in equation (4) which are related to the capital acquisition of medical equipment.

$$\gamma_3 = \phi\ (MinCap,\ CapEqp,\ P_e,\ Uc) \qquad (4)$$

The fixed cost variable, γ_4, is a function of the random variables which are unaffected by a change in volume as illustrated in equation (5).

$$\gamma_4 = \phi\ (Rent,\ Ins,\ Util) \qquad (5)$$

The variable, γ_5, is a function of the random variables which are related to the inflation adjusted discount rate as illustrated in equation (6).

$$\gamma_5 = \phi\ (Inf,\ Prr,\ n) \qquad (6)$$

The variable, γ_6, is a function of the renovation cost (Rc) which is necessitated by upgrading the capital equipment as illustrated in equation (7).

$$\gamma_6 = \phi\ (Rc) \qquad (7)$$

The variable, γ_7, is a function of the capital equipment's future estimated worth as illustrated in equation (8).

$$\gamma_7 = \phi\ (Sv) \qquad (8)$$

Assuming that all the variables are random and continuous, and also that f(i) is the probability density function of the ith variable, the expected value, E[AEC], and the variance, VAR[AEC] of the annual equivalent cost function are given accordingly by equations (9) and (10) respectively [Hahn and Shapiro, 1967; Ang and Tang, 1975].

Furthermore, f(i) di is the probability such that the values of the i^{th} random variable can be found in the range given by i to i+di.

$$E[AEC] = \int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty}\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)*f(\gamma_1)d\gamma_1*f(\gamma_2)d\gamma_2,\ldots,f(\gamma_n)d\gamma_n \qquad (9)$$

Similarly, the expression for VAR[AEC] is given below

$$VAR[AEC] = \int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty}[\phi(\gamma_1)-E(AEC)]^2*[\phi(\gamma_2)-E(AEC)]^2*\ldots*$$
$$[\phi(\gamma_n)-E(AEC)]^2*f(\gamma_1)d\gamma_1*f(\gamma_2)d\gamma_2*,\ldots,*f(\gamma_n)d\gamma_n \qquad (10)$$

Thus, both the expected value and the variance for the AEC can be obtained, and subsequently used, to assess the financial implications from the design and implementation of an option, and the corresponding unit cost of an exam subject to economic and technical constraints. Estimates for the mean and variance of the AEC function can be obtained by expanding equation (1) using Taylor series expansion about the means of the variates.

3.2 The AEC Sensitivity Model

The sensitivity model is derived by employing the method of generating system moments to arrive at estimates for the mean and the variance of the AEC function. Generation of system moments [Frimpong and Whiting, 1992] provides information about the relative importance of each random variable in the AEC function by examining the magnitude of its partial derivative. As a result, more stringent tolerances can be imposed on those random variables that contribute most heavily to the system's overall variability. Many hospital subsystems involve complex operations whose performances fluctuate as a result of variations in their components. Thus, knowledge surrounding these variations permits a greater understanding of the subsystem structure, which allows hospital managers to

redesign a process to be more cost effective, while ensuring adequate delivery and quality services.

Let the relationship between the AEC function and its random variable components be given by equation (1). The exact moments of the AEC function can be obtained as the mathematical expectation of $\phi(\gamma_i)$ where i = 1,2,3,...,7 [Hahn and Shapiro 1967; Ang and Tang 1975]. Let $E(\gamma_i)$ be the expected value for the ith random variable; $E[\gamma_i - E(\gamma_i)]^r$ be the rth moment about the mean of the ith random variable, where r = 2,3,4; E(AEC) be the expected value of the annual equivalent cost function; $E[AEC - E(AEC)]^r$ be the rth moment about the mean of the AEC function.

The first step is to expand $\phi(\gamma_i)$ in equation (1) in a multivariable Taylor series to the second order about $E(\gamma_i)$ as illustrated below in equation (11). A Taylor series expansion to the second order is often a sufficient approximation, because higher order derivatives are usually small in magnitude, and thus, insignificant to explain relative importance among random variables. An error term ε is introduced to reflect the error associated with higher terms. It is simply the difference $\phi(\gamma) - \phi_n(\gamma)$ where $\phi_n(\gamma)$ is the Taylor polynomial of degree n used to approximate $\phi(\gamma)$ near some interval $\phi = a$.

$$\phi(\gamma_1,\gamma_2,\ldots,\gamma_n) = \phi[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)] + \sum_{i=1}^{n}\frac{\partial\phi}{\partial\gamma_i}[\gamma_i - E(\gamma_i)]$$

$$+\frac{1}{2}\left\{\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^2}[\gamma_i - E(\gamma_i)]^2\right.$$

$$\left.+2\sum_{i=1}^{n-1}\sum_{j=2}^{n}\frac{\partial^2\phi}{\partial\gamma_i\partial\gamma_j}[\gamma_i - E(\gamma_i)]*[\gamma_j - E(\gamma_j)]\right\} + \varepsilon \qquad (11)$$

where i≠j

All the derivatives are evaluated at their expected values. The expected value is applied to both sides of equation (11) to yield equation (12).

$$E\left[\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)\right] = E\left\{\phi\left[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)\right]\right\} + E\left\{\sum_{i=1}^{n}\frac{\partial\phi}{\partial\gamma_i}\left[\gamma_i - E(\gamma_i)\right]\right\}$$
$$+ E\left\{\frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^{\,2}}\left[\gamma_i - E(\gamma_i)\right]^2\right\}$$
$$+ E\left\{\sum_{i=1}^{n-1}\sum_{j=2}^{n}\frac{\partial^2\phi}{\partial\gamma_i\partial\gamma_j}\left[\gamma_i - E(\gamma_i)\right]*\left[\gamma_j - E(\gamma_j)\right]\right\} \qquad (12)$$

Each term on the right-hand side of equation (12) is evaluated separately in order to determine the exact moments. The expectation of the first term in equation (12) yields,

$$E\left\{\phi\left[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)\right]\right\} = \phi\left[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)\right] \qquad (13)$$

where E(cγ)=cE(γ), c is any constant. The second term in equation (12) is given by,

$$E\left\{\sum_{i=1}^{n}\frac{\partial\phi}{\partial\gamma_i}\left[\gamma_i - E(\gamma_i)\right]\right\} = \sum_{i=1}^{n}E\left\{\frac{\partial\phi}{\partial\gamma_i}\left[\gamma_i - E(\gamma_i)\right]\right\}$$
$$= \sum_{i=1}^{n}\frac{\partial\phi}{\partial\gamma_i}\left\{E\left[\gamma_i - E(\gamma_i)\right]\right\} \qquad (14)$$

Similarly, the third term in equation (12) yields,

$$E\left\{\frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^{\,2}}\left[\gamma_i - E(\gamma_i)\right]^2\right\} = \frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^{\,2}}E\left[\gamma_i - E(\gamma_i)\right]^2$$
$$= \frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^{\,2}}Var(\gamma_i) \qquad (15)$$

By definition,

$$Var(\gamma_i) = E\left[\gamma_i - E(\gamma_i)\right]^2$$

The last term in equation (12) also yields,

$$E\left\{\sum_{i=1}^{n-1}\sum_{j=2}^{n}\frac{\partial^2\phi}{\partial\gamma_i\partial\gamma_j}\left[\gamma_i - E(\gamma_i)\right]*\left[\gamma_j - E(\gamma_j)\right]\right\} =$$

$$\sum_{i=1}^{n-1}\sum_{j=2}^{n}\frac{\partial^2\phi}{\partial\gamma_i\partial\gamma_j}E\left\{\left[\gamma_i - E(\gamma_i)\right]*\left[\gamma_j - E(\gamma_j)\right]\right\} \qquad (16)$$

Substituting equations (13), (14), (15), and (16) into equation (12) yields an expression for the expected value of the annual equivalent cost function.

$$E[AEC] = \phi[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)] + \frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^2}Var(\gamma_i)$$

$$+\sum_{i=1}^{n-1}\sum_{j=2}^{n}\frac{\partial^2\phi}{\partial\gamma_i\partial\gamma_j}E\left\{\left[\gamma_i - E(\gamma_i)\right]*\left[\gamma_j - E(\gamma_j)\right]\right\} \qquad (17)$$

The second moment about the mean of the AEC function, VAR[AEC], is given by,

$$Var[AEC] = Var\left[\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)\right]$$

$$= E\left[\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)\right]^2 - \left\{E\left[\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)\right]\right\}^2 \qquad (18)$$

The first term in equation (18) is given by,

$$E\left[\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)\right]^2 = \left\{\phi\left[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)\right]\right\}^2$$

$$+\sum_{i=1}^{n}\left(\frac{\partial\phi}{\partial\gamma_i}\right)^2 E\left[(\gamma_i)-E(\gamma_i)\right]^2$$

$$+\phi\left[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)\right]*\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i}E\left[\gamma_i-E(\gamma_i)\right]^2 \qquad (19)$$

The second term in equation (18) is also given by,

$$\left\{E\left[\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)\right]\right\}^2=\left\{\phi\left[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)\right]+\frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^{\,2}}Var(\gamma_i)\right\}^2$$

$$=\left\{\phi\left[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)\right]\right\}^2$$

$$+\phi\left[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)\right]$$

$$*\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^{\,2}}E\left[\gamma_i-E(\gamma_i)\right]^2 \qquad (20)$$

Substituting equations (19) and (20) into equation (18) yields an expression for the variance of the annual equivalent cost function.

$$Var\left[\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)\right]=\sum_{i=1}^{n}\left(\frac{\partial\phi}{\partial\gamma_i}\right)^2 E\left[\gamma_i-E(\gamma_i)\right]^2$$

$$=\sum_{i=1}^{n}\left(\frac{\partial\phi}{\partial\gamma_i}\right)^2 Var(\gamma_i)$$

$$+2\sum_{i=1}^{n-1}\sum_{j=2}^{n}\left(\frac{\partial\phi}{\partial\gamma_i}\right)\left(\frac{\partial\phi}{\partial\gamma_j}\right)E\left\{\left[\gamma_i-E(\gamma_i)\right]*\left[\gamma_j-E(\gamma_j)\right]\right\}$$

$$+\sum_{i=1}^{n}\left(\frac{\partial\phi}{\partial\gamma_i}\right)\left(\frac{\partial^2\phi}{\partial\gamma_i^{\,2}}\right)\mu_3(x_i)+\sum_i\sum_j\left(\frac{\partial\phi}{\partial\gamma_i}\right)\left(\frac{\partial^2\phi}{\partial\gamma_j^{\,2}}\right)*$$

$$+E\left\{\left[\gamma_i-E(\gamma_i)\right]*\left[\gamma_j-E(\gamma_j)\right]^2\right\}$$

$$+2\sum_{i=1}^{n-1}\sum_{j=2}^{n}\left(\frac{\partial\phi}{\partial\gamma_i}\right)\left(\frac{\partial^2\phi}{\partial\gamma_i\partial\gamma_j}\right)E\left\{\left[\gamma_i-E(\gamma_i)\right]^2*\left[\gamma_j-E(\gamma_j)\right]\right\}$$

$$+2\sum_{i}\sum_{j}\sum_{s}\left(\frac{\partial\phi}{\partial\gamma_i}\right)\left(\frac{\partial^2\phi}{\partial\gamma_j\partial\gamma_s}\right)*$$

$$E\left\{\left[\gamma_i-E(\gamma_i)\right]*\left[\gamma_j-E(\gamma_j)\right]*\left[x_s-E(x_s)\right]\right\} \qquad (21)$$

Under the assumption of statistical independence, that is, it is assumed that the random variables are uncorrected, then equations (17) and (21) reduce to

$$E[AEC]=\phi[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)]+\frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2\phi}{\partial\gamma_i^2}Var(\gamma_i)$$

$$=\phi[E(\gamma_1),E(\gamma_2),\ldots,E(\gamma_n)]+BIAS \qquad (22)$$

The BIAS component is the random 'noise' about the expected value of the AEC function. The magnitude of the 'noise' is given by the partial derivative of each random variable in the E[AEC] function shown above in equation (22).

$$Var\left[\phi(\gamma_1,\gamma_2,\ldots,\gamma_n)\right]=\sum_{i=1}^{n}\left(\frac{\partial\phi}{\partial\gamma_i}\right)^2E\left[\gamma_i-E(\gamma_i)\right]^2$$

$$=\sum_{i=1}^{n}\left(\frac{\partial\phi}{\partial\gamma_i}\right)^2Var(\gamma_i) \qquad (23)$$

VARSIM [Griffin and Hamilton,1991; Griffin, 1995] is a general library of routines used to provide numerical estimates for the variance and the BIAS component of the mean estimate for the user-supplied AEC function. Input values for the analysis include the mean and the standard deviation for each of the random variables. The first and second partial derivatives of the AEC function with respect to each variable are estimated numerically to determine the expected value and the variance for the AEC function. *Upon entering the mean and standard deviation for each random variable, the analyst*

can perform the variance and component analyses using the method of moment approximation.

VARSIM provides many advantages which essentially serve to enhance this research study. For instance, one of its strength is to reduce the number of independent variables in the model, and thus, leaving only those random variables which are likely to influence the AEC function. Including all of the independent variables in the model, not only increases run time, but also increases the cost associated with each simulation run. Thus, it is prudent from a resource control perspective to reduce run time, and include only those random variables which are likely to significantly explain the total variation in the AEC function.

3.3 The Stochastic Model of a Generalized Hospital

In the field of hospital capital budgeting, management makes decisions by selecting an option from several competing options. The choice of a design option, in many ways, depends on a number of random variables. In such cases, the appropriate decisions must be the result of simulating random multivariable functions. In order to reduce the cost of the simulation experiment, only the sensitive random variables must be considered at all levels of the decision-making process. In this analysis, the results from the VARSIM analysis will be used as inputs to the stochastic models.

Let $\gamma_1,\gamma_2,\ldots,\gamma_n$ be the sensitive random variables from the VARSIM analysis, that affect the decision-making process and $f(\gamma_1),f(\gamma_2),\ldots,f(\gamma_n)$ the corresponding density function of these variables. Also, this random multivariable function is characterized by the unknown parameters μ and σ. The decision space α, is determined by

$$\alpha = \lambda(\gamma_1,\gamma_2,\ldots,\gamma_n) \qquad (24)$$

λ is the decision space. Whenever, any decision is made, management incurs an opportunity cost. Let the lost opportunity be defined in terms of a loss function [Hines and Montgomery, 1990] determined by

$$\beta(\alpha;\mu,\sigma) = \beta\{\lambda(\gamma_1,\gamma_2,\ldots,\gamma_n);\mu,\sigma\} \tag{25}$$

The risk inherent in the choice of a design option is the expected value of the loss function given by

$$\psi(\lambda;\mu,\sigma) = E\left[\beta\{\lambda(\gamma_1,\gamma_2,\ldots,\gamma_n);\mu,\sigma\}\right]$$

$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\ldots\int_{-\infty}^{\infty}\beta\{\lambda(\gamma_1,\gamma_2,\ldots,\gamma_n)\} * f(\gamma_1)f(\gamma_2)\ldots f(\gamma_n)d\gamma_1 d\gamma_2\ldots d\gamma_n \tag{26}$$

Now suppose $S_1, S_2,\ldots, S_n$ are the sample space for $\gamma_1,\gamma_2,\ldots,\gamma_n$, equation (26) becomes.

$$\psi(\lambda;\mu,\sigma) = \int\int\ldots\int_{S_1}\beta\{\lambda(\gamma_1,\gamma_2,\ldots,\gamma_n);\mu,\sigma\} * f(\gamma_1)f(\gamma_2)\ldots f(\gamma_n)d\gamma_1 d\gamma_2\ldots d\gamma_n$$

$$+ \int\int\ldots\int_{S_2}\beta\{\lambda(\gamma_1,\gamma_2,\ldots,\gamma_n);\mu,\sigma\} * f(\gamma_1)f(\gamma_2)\ldots f(\gamma_n)d\gamma_1 d\gamma_2\ldots d\gamma_n$$

$$+ \int\int\ldots\int_{Sn}\beta\{\lambda(\gamma_1,\gamma_2,\ldots,\gamma_n);\mu,\sigma\} * f(\gamma_1)f(\gamma_2)\ldots f(\gamma_n)d\gamma_1 d\gamma_2\ldots d\gamma_n \tag{27}$$

The decision function is such that α_1 is selected in S_1, α_2 in S_2 and α_n in S_n. Therefore, equation (27) becomes

$$\psi(\lambda;\mu,\sigma) = \int\int\ldots\int_{S_1}\beta(\alpha_1;\mu,\sigma) * f(\gamma_1)f(\gamma_2)\ldots f(\gamma_n)d\gamma_1 d\gamma_2\ldots d\gamma_n$$

$$+ \int\int \ldots \int_{S_2} \beta(\alpha_2;\mu,\sigma) * f(\gamma_1) f(\gamma_2) \ldots f(\gamma_n) d\gamma_1 d\gamma_2 \ldots d\gamma_n$$

$$+ \int\int \ldots \int_{S_n} \beta(\alpha_n;\mu,\sigma) * f(\gamma_1) f(\gamma_2) \ldots f(\gamma_n) d\gamma_1 d\gamma_2 \ldots d\gamma_n$$

$$= \beta(\alpha_1;\mu,\sigma) * P(\gamma_1 \in S_1|\mu,\sigma) + \beta(\alpha_2;\mu,\sigma) * P(\gamma_2 \in S_2|\mu,\sigma) + \ldots$$
$$+ \beta(\alpha_n;\mu,\sigma) * P(\gamma_n \in S_n|\mu,\sigma) \qquad (28)$$

$$\sum_{i=1}^{n} P(\gamma_i \in S_i|\mu,\sigma) = 1.0 \qquad (29)$$

$P(\gamma_n \in S_n|\mu,\sigma)$ is the probability that the sample point γ_i falls in S_i, given that the true mean and standard deviation of the multivariable function are μ and σ, respectively.

For mutually exclusive options, the opportunity lost or gained may be estimated by considering (i) the probability of achieving a higher or lower return than the expectation of management, and (ii) the opportunity lost or gained by making a decision to implement a design option. If $F(a_i)$, [i=1,n] is the cumulative probability distribution function (PDF) of the annual equivalent cost in a Monte Carlo experiment on the design option a_i, then the probability of exceeding a certain minimum cost, $a_{i\,min}$, is given by

$$P(a_i \geq a_{i\,min}) = 1 - F(a_{i\,min}) \qquad (30)$$

If equation (28) is under a certain cut-off limit for any design option, it will be considered among the possible choices. The next stage in the selection process is the examination of the opportunity lost or gained, $\psi(a_i; \mu_i, \sigma_i)$, by selecting any of the design options, a_i.

$$\psi(a_i;\mu_i,\sigma_i)=\begin{cases} E[a_1]*[1-P(a_1)]-Min\{E(a_i)*[1-P(a_i)_{i=2,n}]\} & \forall\, a_1 \\ E[a_2]*[1-P(a_2)]-Min\{E(a_i)*[1-P(a_i)_{i=1,3,4,\ldots,n}]\} & \forall\, a_2 \\ E[a_3]*[1-P(a_3)]-Min\{E(a_i)*[1-P(a_i)_{i=1,2,4,\ldots,n}]\} & \forall\, a_3 \\ \vdots \\ \vdots \\ E[a_n]*[1-P(a_n)]-Min\{E(a_i)*[1-P(a_i)_{i=1,2,\ldots,n-1}]\} & \forall\, a_n \end{cases} \quad (31)$$

The design option with the least value in equation (31) will be recommended for implementation by management. $E[a_i]$ and $P(a_i)$ are obtained through the Monte Carlo simulation technique.

3.3.1 Monte Carlo Simulation Technique (MCST)

The MCST is used in this study to estimate the expected AEC value for the designed options and their associated probabilities. This technique estimates the value of a complex function of multiple integrals by simulating a large number of samples from the cumulative density function of the random variables [Hammersley and Handscomb, 1964; Billinton and Li, 1994; Binder, 1986; Kalos, 1984]. The design, efficiency and convergence characteristics of a Monte Carlo simulation experiment depend on a number of factors. The significant factors include the choice of a variance reduction technique, random variate generation method, and the number of drawn samples [Billinton and Li, 1994]. In this study, discussions will focus only on the mathematical basis of the @Risk software selected for the research experiments.

3.3.2 Variance Reduction Techniques

A number of variance reduction techniques may be used to sample the random variates to carry out the Monte Carlo simulation experiment. These methods include crude, stratified, importance, control variates, antithetic and orthonormal sampling methods

[Hammersley and Handscomb, 1964; Billinton and Li, 1994]. The stochastic simulation in the @Risk software uses the crude and the stratified sampling methods [@Risk, 1996]. In the crude sampling method, a number of independent random numbers, $r_1, r_2, \ldots, r_n$, are generated from various cumulative density functions, and are used to estimate expected value and variance of the AEC function [Hammersley and Handscomb, 1964; Billinton and Li, 1994].

In stratified sampling, the range of integration is divided into several sections, i.e., $\alpha_{i-1} < \gamma \leq \alpha_i$, where $0 = \alpha_0 < \alpha_1 < \alpha_2 \ldots < \alpha_n = 1$. The crude sampling method is then applied to each piece separately. The estimator of the expected value of the AEC function, $\hat{E}[AEC]$, is then given by

$$\hat{E}[AEC] = \sum_{i=1}^{n} \sum_{j=1}^{k} (\alpha_i - \alpha_{i-1}) * \frac{1}{u} \cdot f\left[\alpha_{i-1} + (\alpha_i - \alpha_{i-1}) \cdot r_{ij}\right] \qquad (32)$$

The variance of the estimate after n samples for the ith space is also given by

$$\hat{VAR}[AEC] = \sum_{i=1}^{k} \frac{(\alpha_i - \alpha_{i-1})}{n} \int_{\alpha_{i-1}}^{\alpha_i} f(\gamma)^2 d\gamma - \sum_{i=1}^{k} \frac{1}{n} \left[\int_{\alpha_{i-1}}^{\alpha_i} f(\gamma)\, d\gamma \right]^2 \qquad (33)$$

Stratified sampling is about ten times as efficient as the crude sampling with an appropriate choice of α_i [Billinton and Li, 1994]. α_i may be selected by dividing i into equal sections or by choosing α_i such that the variation of $f(\gamma)$ is the same in each piece [Hammersley and Handscomb, 1964; Billinton and Li, 1994].

3.3.3 Random Variate Generation

Stochastic simulation via the Monte Carlo simulation technique (MCST) is achieved by generating a large number of random samples from cumulative density functions in each of the sampling methods. Generation of the random samples is also achieved by using

the inverse transform, composition, and accept-reject methods [Billinton and Li, 1994; Binder, 1986]. If a random variable R follows a uniform distribution in the interval [0,1], the inverse transform method states that the random variable $X = F^{-1}(R)$ has a continuous cumulative probability density function F(γ).

The inverse transform algorithm proceeds as follows:

(i) Generate a uniformly distributed random number sequence R between [0,1].

(ii) Calculate the random variable which has the F(γ) as $X = F^{-1}(R)$ as illustrated in Figure 3.1.

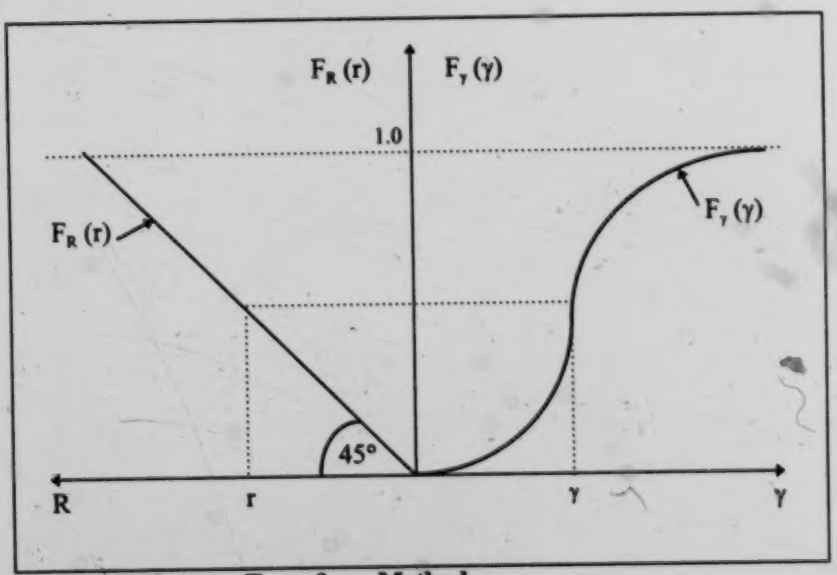


Figure 3.1: Inverse Transform Method.

In this research study, the stochastic simulation is achieved by generating random samples from the normal, lognormal and triangular distributions. The following is a brief discussion of the algorithmic procedures for achieving the random variate sampling from the normal and triangular distributions.

3.3.3.1 Generating Normally Distributed Random Variates

The variables, Medfee, Medsal, Relstaff, Conmed, Radiology, and Drugs of the AEC function are described by the normal distribution. The random variates from this distribution can be generated by the approximate inverse transform or the Box-Muller Methods [Billinton and Li, 1994; Binder, 1986]. A random variable γ has a normal distribution if the probability density function is

$$f(\gamma) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\frac{\gamma-\mu}{\sigma}\right)^2\right] \qquad (34)$$

$$-\infty \le \gamma \le \infty; \quad -\infty \le \gamma \le \infty; \quad \sigma \ge 0$$

From Box and Miller (1958) and Frimpong (1992), if u_1 and u_2 are two independent and standard uniform variates, then equation (35) and (36) constitute a pair of statistically independent standard normal variates.

$$S_1 = \left(-2\ ln\ u_1\right)^{1/2}\ cos\ 2\pi\ u_2 \qquad (35)$$

$$S_2 = \left(-2\ ln\ u_1\right)^{1/2}\ sin\ 2\pi\ u_2 \qquad (36)$$

If substituting $U = -ln\ u_1$ and $V = u_2$ into equation (35) and (36) and obtaining these equations in terms of U and V, the Jacobian of the transformation is given by

$$J = \begin{vmatrix} \frac{\partial u}{\partial S_1} & \frac{\partial u}{\partial S_2} \\ \frac{\partial v}{\partial S_1} & \frac{\partial v}{\partial S_2} \end{vmatrix} = \begin{vmatrix} S_1 & S_2 \\ \frac{-S_2}{2\pi\left(S_1^2 + S_2^2\right)} & \frac{S_1}{2\pi\left(S_1^2 + S_2^2\right)} \end{vmatrix} = \frac{1}{2\pi} \qquad (37)$$

The joint PDF from Frimpong (1992) is then given by

$$f(S_1,S_2) = f(u,v)\cdot|J| = \frac{1}{2\pi}exp\left[-\frac{1}{2}\left(S_1^2 + S_2^2\right)\right] \qquad (38)$$

$$-\infty < S_1 \text{ and } S_2 < \infty$$

Equation (38) is the joint PDF of two independent standard normal variates. Therefore, if u_1 and u_2 are a pair of independent uniformly distributed random numbers, a pair of independent random numbers from $N(\mu,\sigma)$ may be generated from equations (39) and (40) as:

$$\gamma_1 = \mu + \sigma*(-2\ln u_1)^{1/2}\cos 2\pi u_2 \qquad (39)$$

$$\gamma_2 = \mu + \sigma*(-2\ln u_1)^{1/2}\sin 2\pi u_2 \qquad (40)$$

The procedure for this algorithm is to generate two uniformly distributed random number sequences between [0,1] and estimating u_1 and u_2 from equations (39) and (40). The lognormal distribution is similar except that the random variate γ is replaced by the natural log of γ in equation (34). The mean and variance of the lognormal distribution are also different [Hines and Montgomery, 1990]. The variable Regest of the AEC function is described by the lognormal distribution.

3.3.3.2 Generating Triangularly-Distributed Random Variates

The variable SV of the AEC function is described by the triangular distribution. If a, m and b are the minimum, mode and maximum values of the density function, then the triangular distribution, $f(\gamma)$, is given by

$$f(\gamma)=\begin{cases}\dfrac{2(\gamma-a)}{(m-a)(b-a)} & a\le\gamma\le m\\[2ex] \dfrac{2(b-\gamma)}{(b-m)(b-a)} & m\le\gamma\le b\end{cases} \qquad (41)$$

By the inverse transform method, the random variable $R=F(\gamma_i)$ is uniformly distributed in the interval [0,1]. The cumulative PDF, $F(\gamma)$, is also divided into two parts as illustrated in equation (42) [Frimpong, 1992].

$$F(\gamma)=\int_a^m f(\gamma)d\gamma+\int_m^b f(\gamma)d\gamma=F_1(\gamma)+F_2(\gamma) \qquad (42)$$

The random samples drawn from $F_1(\gamma)$, $r_i(1)$, follow the following equation

$$r_i(1)=F_1(\gamma)=\begin{cases}0 & \forall\ \gamma=a\\[2ex] \dfrac{(n-a)^2}{(m-a)(b-a)} & \forall\ a<\gamma<m\\[2ex] \dfrac{m-a}{b-a} & \forall\ \gamma=m\end{cases} \qquad (43)$$

The random variate, $\gamma_i(1)$, is also given by

$$\gamma_i(1)=a+\left[r_i(1)*(m-a)(b-a)\right]^{1/2} \qquad (44)$$

The random samples drawn from $F_2(\gamma)$, $r_i(2)$, follow the following equation

$$r_i(2) = F_2(\gamma) = \begin{cases} \dfrac{m-a}{b-a} & \forall\ \gamma = m \\ \dfrac{(2b-n)n + m(a-b) - ab}{(b-m)(b-a)} & \forall\ m < \gamma < b \\ 1 & \forall\ n = b \end{cases} \qquad (45)$$

The random variate, $\gamma_i(2)$, is also given by

$$\gamma_i(2) = b - \left[(1 - r_i(2)) * (b-m) * (b-a)\right]^{1/2} \qquad (46)$$

For known values of a, m and b, random numbers between [0,1] could be used to obtain samples $\gamma_i(1)$ and $\gamma_i(2)$ in equation (44) and (46) from the triangular distribution.

3.4 Efficiency and Convergence Characteristics of the MCST

In addition to a large number of random sampling, the efficiency of the MCST depends on the CPU time, t and the variance of the estimate [Hammersley and Handscomb, 1964; Billinton and Li, 1994; Winkler, 1995].

$$\eta = t\,\sigma^2 \qquad (45)$$

If the ratio of the efficiencies of two methods is such that

$$R = \frac{\eta_1}{\eta_2} = \frac{t_1\,\sigma_1^2}{t_2\,\sigma_2^2} < 1.0 \qquad (46)$$

method 1 is more efficient than method 2. The error bound in Monte Carlo estimate decreases as the number of samples increases. The standard error of the estimate, σ_e, is obtained as follows:

$$\sigma_e = (VAR)^{1/2} / (N)^{1/2} \qquad (47)$$

From equation (31), it is necessary to utilize a reasonable and sufficiently large number of samples to reduce σ_e, since, it is always difficult to reduce the variance to zero. At a certain critical point, the value added does not warrant the long CPU time by increasing the number of samples.

3.5 A VARSIM Example of The UES Option

A numerical example of the functional moment methodology is carried out for the UES option. The functional model for the UES option is given by equation (48).

$$\begin{aligned} AEC(UES) = \{ & (medfee + medsal + relstaff + prepay + regest + ad\ min + empben) \\ & * \left[\frac{1-(1+g)^n (1+i)^{-n}}{i-g} \right] \\ & + (medsurg + conmed + drug + radio\ log\ y + conmain + other) \\ & * \left[\frac{1-(1+g)^n (1+i)^{-n}}{i-g} \right] \\ & + fixed * \left[\frac{1-(1+g)^n (1+i)^{-n}}{i-g} \right] + capital \} * \left[\frac{i(1+i)^n}{(1+i)^n - 1} \right] \\ & - salvage * \left[\frac{i}{(1+i)^n - 1} \right] \end{aligned} \qquad (48)$$

Based on equations (22) and (23), the expected value, E[AEC(UES)], and the variance, Var[AEC(UES)] for the UES design option are obtained respectively.

$$E[AEC(UES)] \cong \begin{bmatrix} E\{medfee, medsal, relstaff, prepay, regest, ad\ min, empben, \\ medsurg, conmed, drugs, radio\ log\ y, conmain, other, \\ fixed, capital, salvage\} \end{bmatrix}$$

$$+\frac{1}{2}\frac{\partial^2\phi}{\partial_{medfee}^{\ 2}}Var(medfee)+\frac{1}{2}\frac{\partial^2\phi}{\partial_{medsal}^{\ 2}}Var(medsal)$$

$$+\frac{1}{2}\frac{\partial^2\phi}{\partial_{relstaff}^{\ 2}}Var(relstaff)+\frac{1}{2}\frac{\partial^2\phi}{\partial_{prepay}^{\ 2}}Var(prepay)$$

$$+\frac{1}{2}\frac{\partial^2\phi}{\partial_{regest}^{\ 2}}Var(regest)+\ldots+\frac{1}{2}\frac{\partial^2\phi}{\partial_{salvage}^{\ 2}}Var(salvage) \qquad (49)$$

Since the system performance is a linear function of the component variables, an exact result is obtained for the E[AEC(UES)] because all second and higher order partial derivatives are zero. Thus, the E[AEC(UES)] is given by

$$E[AEC(UES)] = \{ \begin{pmatrix} E[medfee] + E[medsal] + E[relstaff] + E[prepay] \\ + E[regest] + E[ad\ min] + E[empben] \end{pmatrix}$$

$$*\left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g}\right]$$

$$+\begin{pmatrix} E[medsurg] + E[conmed] + E[drug] + E[radio\ log\ y] \\ + E[conmain] + E[other] \end{pmatrix}$$

$$*\left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g}\right]$$

$$+ E[fixed]*\left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g}\right] + E[capital]\}$$

$$*\left[\frac{i(1+i)^n}{(1+i)^n-1}\right] - E[salvage]*\left[\frac{i}{(1+i)^n-1}\right] \qquad (50)$$

The geometric gradient, g, in the above equation accounts for increases over time for labor, supplies, and fixed costs. It is important to recognize that the rate of increase is different among these costs. The variable n represents the project life which for this

research study is five years, while the inflation adjusted discount rate given by i is 12.39 percent. The expected values and variances for the functional model are given in Table 6.1 found in Section 6.1.1. Substituting the expected values for the variables yield

$$E[AEC(UES)] = \left\{ \begin{pmatrix} 1{,}190{,}700 + 60{,}011 + 64{,}417 + 20{,}158 + 563{,}082 \\ + 71{,}561 + 91{,}565 \end{pmatrix} * \left[\frac{1-(1+0.03)^{5}(1+0.1239)^{-5}}{0.1239-0.03} \right] \right.$$

$$+ (5{,}799 + 103{,}959 + 10{,}474 + 130{,}501 + 176{,}819 + 71{,}945) * \left[\frac{1-(1+0.10)^{5}(1+0.1239)^{-5}}{0.1239-0.10} \right]$$

$$+ 582{,}014 * \left[\frac{1-(1+0.05)^{5}(1+0.1239)^{-5}}{0.1239-0.05} \right]$$

$$\left. + 3{,}000{,}000 \right\} * \left[\frac{0.1239(1.1239)^{5}}{(1.1239)^{5}-1} \right]$$

$$- 400{,}000 * \left[\frac{0.1239}{(1.1239)^{5}-1} \right]$$

$$\cong \$4{,}184{,}265 \text{ per year}$$

The annual target number of MRI exams used in this research is 11,907. Thus, the AEC when expressed per unit of output is $351 per exam.

The Var[AEC(UES)] is given by

$$Var[AEC(UES)] \cong \left(\frac{\partial \phi}{\partial_{medfee}}\right)^2 Var(medfee) + \left(\frac{\partial \phi}{\partial_{medsal}}\right)^2 Var(medsal)$$
$$+ \left(\frac{\partial \phi}{\partial_{relstaff}}\right)^2 Var(relstaff) + \left(\frac{\partial \phi}{\partial_{regest}}\right)^2 Var(regest)$$
$$+ \left(\frac{\partial \phi}{\partial_{conmed}}\right)^2 Var(conmed) + \left(\frac{\partial \phi}{\partial_{drugs}}\right)^2 Var(drugs)$$
$$+ \left(\frac{\partial \phi}{\partial_{radio\ log\ y}}\right)^2 Var(radio\ log\ y) \qquad (51)$$

Again, since the partial derivatives for second and higher order derivatives are zero, then under the assumption of independence, Var[AEC(UES)], is obtained by adding the variances of the individual components. Substituting estimates for the component variances yield

$$Var[AEC(UES)] \cong Var(medfee) + Var(medsal) + Var(relstaff) + Var(regest)$$
$$+ Var(conmed) + Var(drugs) + Var(radio\ log\ y)$$
$$\cong \left\{\begin{matrix} 156{,}334^2 + 6{,}001^2 + 19{,}003^2 + 187{,}506^2 + 10{,}396^2 \\ + 1{,}047^2 + 26{,}100^2 \end{matrix}\right\}$$
$$\cong 6.08e10\ (\$ / year)^2$$

$$std.dev \cong \sqrt{6.08e10}$$
$$\cong \$246{,}577\ per\ year$$

When expressed per unit of output, the standard deviation becomes $20.7 per exam.

3.6 A VARSIM Example of The LCE Option

A numerical example of the functional moment methodology is carried out for the LCE option. The functional model for the LCE option is given by equation (52).

$$AEC(UES) = \{ (medfee + medsal + relstaff + prepay + regest + ad\ min + empben) * \left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g}\right] + (medsurg + conmed + drug + radio\ log\ y + conmain + other) * \left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g}\right] + fixed * \left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g}\right] \} * \left[\frac{i(1+i)^n}{(1+i)^n-1}\right] + lease - salvage * \left[\frac{i}{(1+i)^n-1}\right] \quad (52)$$

The expected value, E[AEC(LCE)], and the variance, Var[AEC(LCE)] for the LCE design option are obtained respectively.

$$E[AEC(LCE)] \cong \begin{bmatrix} E\{medfee, medsal, relstaff, prepay, regest, ad\ min, empben, \\ medsurg, conmed, drugs, radio\ log\ y, conmain, other, \\ fixed, lease, salvage\} \end{bmatrix} + \frac{1}{2}\frac{\partial^2\phi}{\partial_{medfee}^{\ 2}}Var(medfee) + \frac{1}{2}\frac{\partial^2\phi}{\partial_{medsal}^{\ 2}}Var(medsal) + \frac{1}{2}\frac{\partial^2\phi}{\partial_{relstaff}^{\ 2}}Var(relstaff) + \frac{1}{2}\frac{\partial^2\phi}{\partial_{prepay}^{\ 2}}Var(prepay) + \frac{1}{2}\frac{\partial^2\phi}{\partial_{regest}^{\ 2}}Var(regest) + \ldots + \frac{1}{2}\frac{\partial^2\phi}{\partial_{salvage}^{\ 2}}Var(salvage) \quad (53)$$

Again, since the system performance is a linear function of the component variables, an exact result is obtained for the E[AEC(LCE)] because all second and higher order partial derivatives are zero. Thus, the E[AEC(LCE)] is given by

$$E[AEC(LCE)] = \left\{ \begin{pmatrix} E[medfee] + E[medsal] + E[relstaff] + E[prepay] \\ + E[regest] + E[ad\ min] + E[empben] \end{pmatrix} * \left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g} \right] \right.$$

$$+ \begin{pmatrix} E[medsurg] + E[conmed] + E[drug] + E[radio\ log\ y] \\ + E[conmain] + E[other] \end{pmatrix} * \left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g} \right]$$

$$\left. + E[fixed] * \left[\frac{1-(1+g)^n(1+i)^{-n}}{i-g} \right] \right\}$$

$$* \left[\frac{i(1+i)^n}{(1+i)^n - 1} \right] + E[lease] - E[salvage] * \left[\frac{i}{(1+i)^n - 1} \right] \qquad (54)$$

The expected values and variances for the functional model are given in Table 6.13 found in Section 6.5.1. Substituting the expected values in equation (54) yield

$$E[AEC(LCE)] = \left\{ \begin{pmatrix} 1{,}190{,}700 + 60{,}011 + 64{,}417 + 20{,}158 + 563{,}082 \\ + 71{,}561 + 91{,}565 \end{pmatrix} * \left[\frac{1-(1+0.03)^5(1+0.1239)^{-5}}{0.1239-0.03} \right] \right.$$

$$+ (5{,}799 + 103{,}959 + 10{,}474 + 130{,}501 + 176{,}819 + 71{,}945) * \left[\frac{1-(1+0.10)^5(1+0.1239)^{-5}}{0.1239-0.10} \right]$$

$$\left. + 582{,}014 * \left[\frac{1-(1+0.05)^5(1+0.1239)^{-5}}{0.1239-0.05} \right] \right\}$$

$$* \left[\frac{0.1239(1.1239)^5}{(1.1239)^5 - 1} \right] + 1{,}020{,}000 - 400{,}000 * \left[\frac{0.1239}{(1.1239)^5 - 1} \right]$$

$$\cong \$4{,}356{,}358$$

The AEC when expressed per unit of output results in a cost of $366 per exam.

The Var[AEC(LCE)] is given by

$$Var[AEC(LCE)] \cong \left(\frac{\partial \phi}{\partial_{medfee}}\right)^2 Var(medfee) + \left(\frac{\partial \phi}{\partial_{medsal}}\right)^2 Var(medsal)$$
$$+ \left(\frac{\partial \phi}{\partial_{relstaff}}\right)^2 Var(relstaff) + \left(\frac{\partial \phi}{\partial_{regest}}\right)^2 Var(regest)$$
$$+ \left(\frac{\partial \phi}{\partial_{conmed}}\right)^2 Var(conmed) + \left(\frac{\partial \phi}{\partial_{drugs}}\right)^2 Var(drugs)$$
$$+ \left(\frac{\partial \phi}{\partial_{radio\ log\ y}}\right)^2 Var(radio\ log\ y) \qquad (55)$$

Again, since the partial derivatives for second and higher order derivatives are zero, then under the assumption of independence, Var[AEC(LCE)], is obtained by adding the variances of the individual components. Substituting estimates for the component variances yield

$$Var[AEC(LCE)] \cong Var(medfee) + Var(medsal) + Var(relstaff) + Var(regest)$$
$$+ Var(conmed) + Var(drugs) + Var(radio\ log\ y)$$
$$\cong \left\{\begin{matrix} 156{,}334^2 + 6{,}001^2 + 19{,}003^2 + 187{,}506^2 + 10{,}396^2 \\ + 1{,}047^2 + 26{,}100^2 \end{matrix}\right\}$$
$$\cong 6.08e10\ (\$ / year)^2$$

$$std.dev \cong \sqrt{6.08e10}$$
$$\cong \$246{,}577\ per\ year$$

When expressed per unit of output, the standard deviation becomes $20.7 per exam.

The expected values and variances of the AEC function for both the UES and LCE design options are compared to the results obtained from the VARSIM output shown in Chapter 6.0, Section 6.1.1 and 6.5.1 of this report. The results from the numerical and computer models compare favorably within 0.06. These results are shown in Table 3.1.

Table 3.1: Functional Moment Methodology Comparisons

	Computed Numerical Example		**VARSIM Output**		**% Difference**	
Design Option	E[AEC] per exam, μ_A	Std.Dev per exam, σ_A	E[AEC] per exam, μ_B	Std.Dev per exam, σ_B	$\frac{\mu_A-\mu_B}{\mu_B}*100$	$\frac{\sigma_A-\sigma_B}{\sigma_B}*100$
UES	$351	20.7	$350	21.9	0.29	5.8
LCE	$366	20.7	$365	21.9	0.29	5.8

3.7 Conclusion

The mathematical modeling of a generalized capital budgeting process developed in this research to solve Hospital's A MRI problem includes: functional, the sensitivity, and stochastic models. Equations are developed to solve for the AEC of each proposed design options. In addition, the underlying decision theory is established for selecting an appropriate design option to be recommended for implementation. A numerical example of the functional moment methodology is carried out for upgrading existing system (UES) and lease capital equipment (LCE) design options. The numerical solutions for these two examples agree with those obtained from the VARSIM analysis.

CHAPTER 4.0
STRUCTURAL DESIGN OPTIONS FOR IMPROVING MRI SYSTEM PERFORMANCE

In this study, seven design options are being considered in order to resolve issues surrounding the wait list associated with the existing MRI operation at Hospital A. These design options are intended to help Hospital A minimize both the current wait list and the annual equivalent cost (AEC) for a magnetic resonance imaging (MRI) exam, while ensuring the delivery of quality service.

Minimizing the current wait list is a function of several elements such as equipment utilization, process efficiency, throughput, and cost minimization. For instance, increasing equipment utilization directly results in increased throughput. In other words, if Hospital A can process MRI patients expediently, further medical intervention can be administered earlier in the patient's treatment. Equally important to the MRI's process is improving its efficiency, which is accomplished by eliminating non-value added services, and reducing cost drivers.

4.1 Introduction

A design option has the capability to assist decision-makers accomplish a stated objective under the existing political and economic climate. The design option is subject to specific structural elements which are comprised of both internal and external influences being exerted on the system. These influences dictate the technical, and economic parameters of a particular design option.

It is necessary to implement an economic design option which achieves the objective set forth by hospital management under the existing political and economic climate. The existing climate is one of fiscal constraint where use of resources is under tremendous scrutiny. The availability of resources is not only scarce, but in some instances, may be restricted to a specific application. In fact, hospitals have experienced a reduction in

funding to all segments of its operation. With an emphasis placed on cost reductions, it becomes even more critical that the selection of a design option minimizes the cost-of-service, and yet ensures that an acceptable level of service is provided to patients. It is important that an element of quality [Deming, 1986] is factored into the design option, otherwise, the potential for rework can result in an increase in operating cost.

The design options under consideration are intended to satisfy the demand for a particular health region. In this research, a health region represents a specific geographical boundary as defined by the Provincial Health Agency [HSFAC, 1995]. For example, the province of Alberta is divided into 17 health regions. Each region is governed by a series of specific mandates to ensure that Canadians receive quality health services in a timely fashion. A newly-proposed health funding system based on the mix in population is the primary reason for having different health regions. The proposed funding system is appropriately called Population Based Funding, because its purpose is to recognize and address the need of people residing in different regions of Alberta. In other words, citizens residing in different health regions are expected to consume health resources at varying rates. For instance, citizens residing in the Northern region of the province, consume resources at a higher level, as compared to those residing in central and southern health regions. Hospital A is located in the central region of the province known as Health Region A, and services a population of approximately 1.4 million Albertans which includes rural and urban centres [HSFAC, 1995].

4.1.1 Current State of The MRI System

The magnetic resonance imaging, also known as nuclear magnetic resonance (NMR), provides clinically relevant anatomic and functional information noninvasively and with minimal risk. It employs powerful magnets to scan any part of the human body. Computer-generated pictures of these scans assist radiologists to identify with accuracy, damaged soft tissues areas of the body where conventional methods are inadequate to make such accurate detection. For example, an MRI exam can identify damage from a heart-attack, diagnose certain congenital heart defects and evaluate disease of larger blood

vessels such as the aorta. An MRI is also able to define problems created by stroke (i.e., brain attack) [AHA, 1996]. The MRI operation at Hospital A has been in existence since 1992. The MRI operation caters to a service population of approximately 1.4 million people, plus additional patients from outside the service catchment area. An expected value of 4,725 MRI exams are carried out by Hospital A annually. Eighty-five percent of those exams performed on head and spinal regions, and slightly more than 10 percent are related to bone and joint disorders. The wait list associated with the existing operation consists of approximately 1,000 patients. These patients are likely to wait about six months for an MRI exam. In an effort to reduce its wait list, Hospital A has contracted another health region to perform about 330 MRI exams annually [Pedersen, 1997]. The MRI information collected and presented in this research pertains to 50 operating hours per week. However, in the last year, these operating hours have increased to approximately 80 hours per week [CHA, 1995]. Figure 4.1 illustrates the process flow of the MRI system.

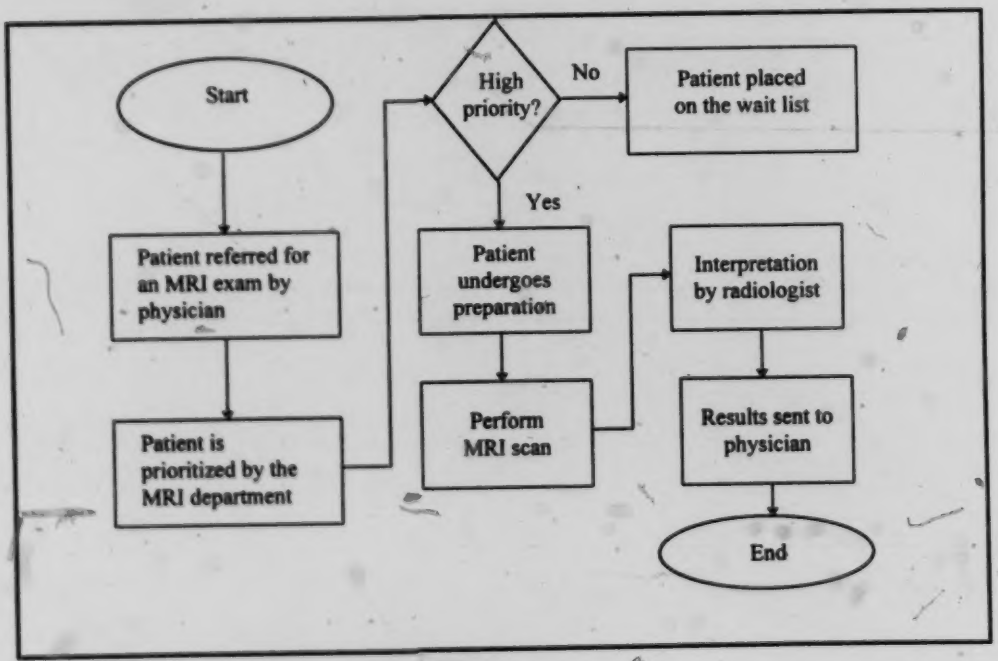
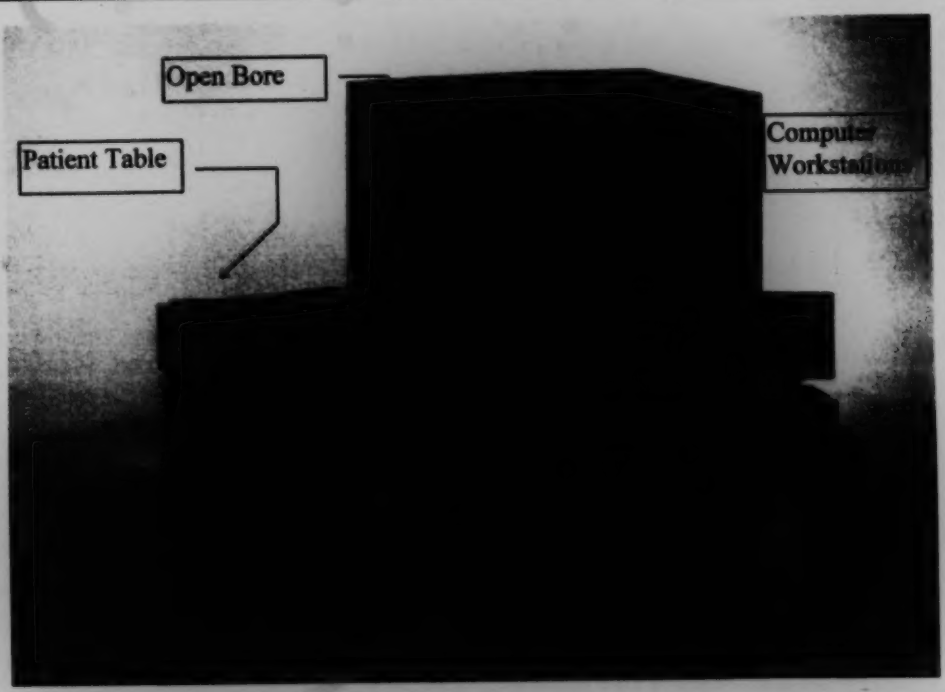


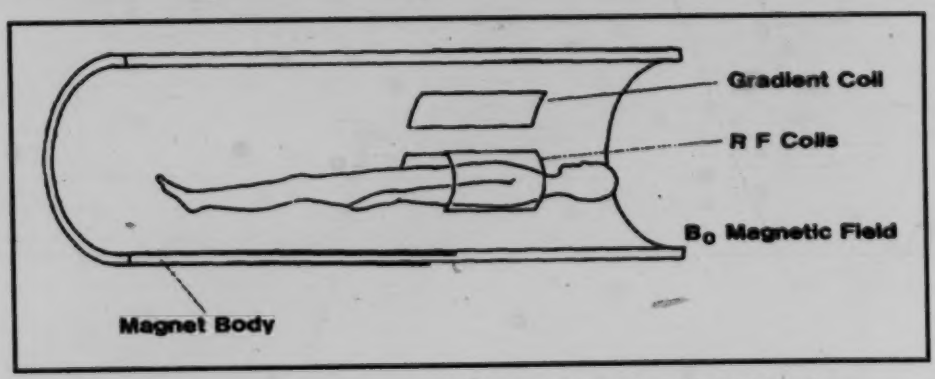
Figure 4.1: Process Flow For An MRI Exam

Patients must first seek a referral by a specialist for an MRI exam. Next, they are prioritized by a radiologist based on an established set of guidelines. A patient classified as priority one receives an MRI exam within 48 hours, whereas a priority three and four patients are immediately placed on the wait list. Typically, priority one cases are urgent and they involve preoperative and acutely-ill patients who receive highest priority, when it is deemed that an MRI provides the most beneficial information, compared to other imaging techniques. In comparison, priority four patients are those who will receive little or no treatment even after the diagnosis. In addition, priority ranking is dependent upon the relevant patient history provided on the requisition form by the patient's physician. Patients receive preparation such as outfitting with necessary gowns and are also sedated, if necessary. Once the scan is completed, a radiologist interprets its results and forwards it to the patient's physician. Figure 4.2 illustrates an MRI scanner system.

The MRI system at Hospital A consists of a 1.5 Tesla Philips MRI scanner, two Gyroview HR 660C workstations, Kodak laser camera and film processor and related accessory equipment. On average, the MRI can conduct 1.89 exams per hour; each exam is carried out during a specific time block. Time blocks are scheduled at either 30 or 45 minute intervals. The duration of the MRI scan is largely dependent on the nature of the exam requested. For instance, a patient requiring an extensive body scan is likely to be scheduled for a 45 minute time block. Although, it must be pointed out, that approximately 40 percent of the total time allotted for an MRI is devoted to patient preparation. As shown in Figure 4.2 (a), the patient is placed on the patient table and then is guided through the MRI's opening called the open bore and into the tunnel. Figure 4.2 (b) illustrates the patient inside the MRI tunnel. The magnet body provides an external magnetic field along the human body axis. Gradient coils provide a smaller identification field. The external magnetic field together with the gradient field produces a net external magnetic field, B_o. The radio frequency (RF) signals impart forces to alter the direction of the magnetic field in order to help create scanned images of various parts of the human body [Juhl and Crummy, 1993].



(a) MRI System Components [Siemens, 1997]



(b) Schematic View of a Patient Inside the Magnetic Field Coils [Juhl and Crummy, 1993]

Figure 4.2: An MRI Scanner System

The MRI scanner is relatively reliable; equipment availability, as quoted by the supplier, is approximately 98-99 percent, outside of scheduled maintenance. However, the reliability of this highly computerized scanner is dependent on a regimented preventative maintenance program, which requires that necessary upgrades to the system are performed. Thus, an adequately maintained MRI system is expected to perform at this level of reliability over the next five years. In fact, an MRI can physically operate seven days a week for a total of 141 hours from a possible 144 hours. One day is set aside for scheduled maintenance. Ten working days are allotted to maintenance annually. Maintenance is not expected to rise significantly with increased operating hours or any increase in maintenance is expected to be marginal.

The interactions between the existing MRI system, Hospital A and the Province are presented in Figure 4.3. Under the current economic climate, Hospital A is able to provide an MRI scan for $569 per exam which represents the full cost (i.e., direct and indirect costs). This particular cost structure is expected to increase exponentially, unless very specific actions are taken to alleviate compounding costs. For example, costs are certain to increase as a result of technological obsolescence and frequent repairs. As technology advances, it is likely that certain MRI components would not be readily available. In the event of a major breakdown, the MRI would remain idle until appropriate parts are located. When the system is idle for any significant length of time, it is inevitable that such disruptions would create a backlog of patients awaiting their MRI exams. Furthermore, patients on the existing MRI wait list are expected to wait even longer for an exam. In fact, the hospital system as a whole is likely to experience a rippling effect when the MRI is idle. For instance, without adequate diagnostic information, trauma victims cannot receive complete patient care which results in a slow recovery process. Other hospital departments are going to face similar patient care problems. Patients with multiple bone fractures are not able to receive an accurate assessment of their injuries, until an MRI can be performed and without this information, the orthopedic department cannot proceed with complete patient care.

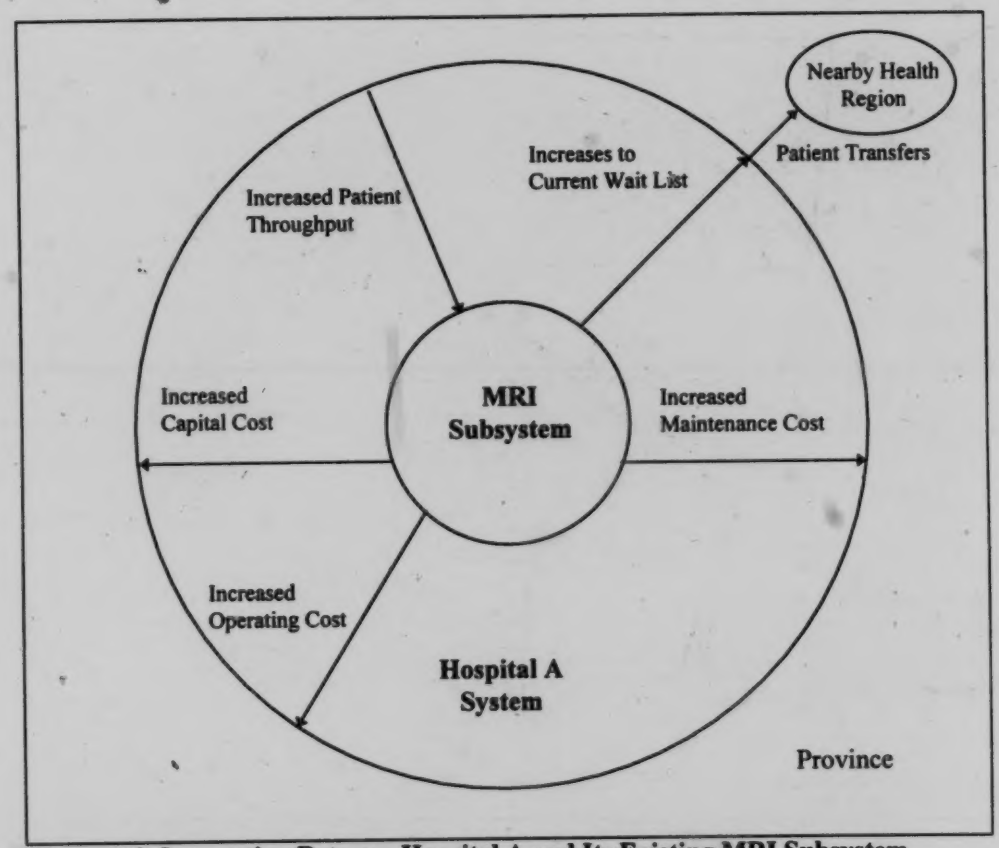


Figure 4.3 Interaction Between Hospital A and Its Existing MRI Subsystem

With all the problems discussed above, maintenance costs are expected to increase significantly because the MRI department recognizes that patient throughput is adversely affected, and thus, must commit to spending aggressively to resolve process problems quickly. This could also lead to increased capital expenditures which are intended to ensure that existing capacities are met. Hospital A is obligated to commit sufficient resources to capital spending in order to minimize downtime. In other words, specific capital expenses are incurred to stabilize the system. Otherwise, the MRI system would perpetuate and magnify problems elsewhere in the hospital if the system is allowed to deteriorate. Increases in maintenance and capital costs both lead to overall increased operating costs which can certainly lead to operating deficits within the MRI department. The MRI system is not self-sufficient, that is, it cannot generate outside revenues to offset

operating deficits. Thus, Hospital A is forced to fund any operating deficits which means that other departments are likely to encounter reduced operating budgets.

In the short-term, operating costs are expected to rise steadily as a result of performing timely repairs and committing to spending sufficiently to sustain current levels of operations. However, in the long-term, cost increases are expected to significantly impact Hospital A's operating budget. As the MRI system ages, it becomes susceptible to increased downtime which is certain to affect patient throughput. Constant interruptions to patient throughput will ultimately cause an upward shift in the number of patients on the current wait list. In addition, patients are going to experience a waiting period closer to one year. To avoid an excessive backlog of patients on the wait list, Hospital A is faced with transferring a larger number of patients to another health region. Surely additional costs such as transportation are incurred with patient transfers. Also, a certain level of inconvenience is bound to affect patients, especially the elderly. In summary, as the MRI system ages due to technological obsolescence, operating, capital and maintenance costs are expected to increase sharply. Furthermore, the number of patients and the waiting period will experience steep increases. The overall hospital system is likely to experience patient care and throughput problems resulting from the inefficient operation of the MRI system

4.2 Design Options

In this research, seven design options and their variants are used to solve the MRI problem in Hospital A. These seven design options include: 1) upgrade existing system (UES), 2) computed axial tomography (CAT), 3) contract another region (CAR), 4) contract private operator (CPO), 5) lease capital equipment (LCE), 6) contract another hospital (CAH), and 7) contract mobile operator (CMO). A further discussion of each design option is presented to provide an insight into the internal and external elements and their interactions in the system. It is assumed that the existing MRI operation at Hospital A would continue to function at its current level. Any one of the options implemented would simply enhance current operations so that strategic targets can be

met. However, it is important to note that each design is accompanied by its own unique cost structure. Thus, careful attention must be given to ensure that a cost-effective option is selected to solve Hospital A's MRI problems. The analysis period for all of the design options is five years.

4.3 Upgrade Existing System (UES) Option

The first design option is to upgrade the existing system (UES) at Hospital A, i.e., performing hardware and software upgrades to Hospital A's MRI system. Upgrading the existing MRI system permits hospital managers to increase operating hours per day from h_1 to h_2. Furthermore, the MRI would operate from its existing number of days per week denoted by d_1 to a new level d_2. It is anticipated that an increase in utilization of the MRI equipment would result in a reduced cost per case from c_1 to a new cost structure denoted by c_2. Cost per case is expected to decline, because a significant portion of the MRI's fixed cost would be allocated over a larger number of exams denoted by Q, which is the target annual MRI exams. More importantly, performing the necessary upgrades would enable Hospital A to attain its annual target of MRI exams Q. Total MRI exams would increase from q_1 to q_2, where ($Q = q_1 + q_2$). Figure 4.4 illustrates the interaction between Hospital A and its MRI subsystem.

From Figure 4.4, it can be seen that operating and maintenance costs are both reduced, while capital cost increases, which are all a direct result of performing the necessary upgrades to the MRI subsystem. Although maintenance cost is included in total operating cost, it is shown separately to emphasize its significance relative to total operating cost. MRI equipment upgrades will allow Hospital A to increase patient throughput to the MRI department, because of the newly available capacity. Furthermore, the excess capacity enables the MRI subsystem to process a number of patients on the current wait list. The overall effect is increased equipment utilization and a reduction to the existing wait list.

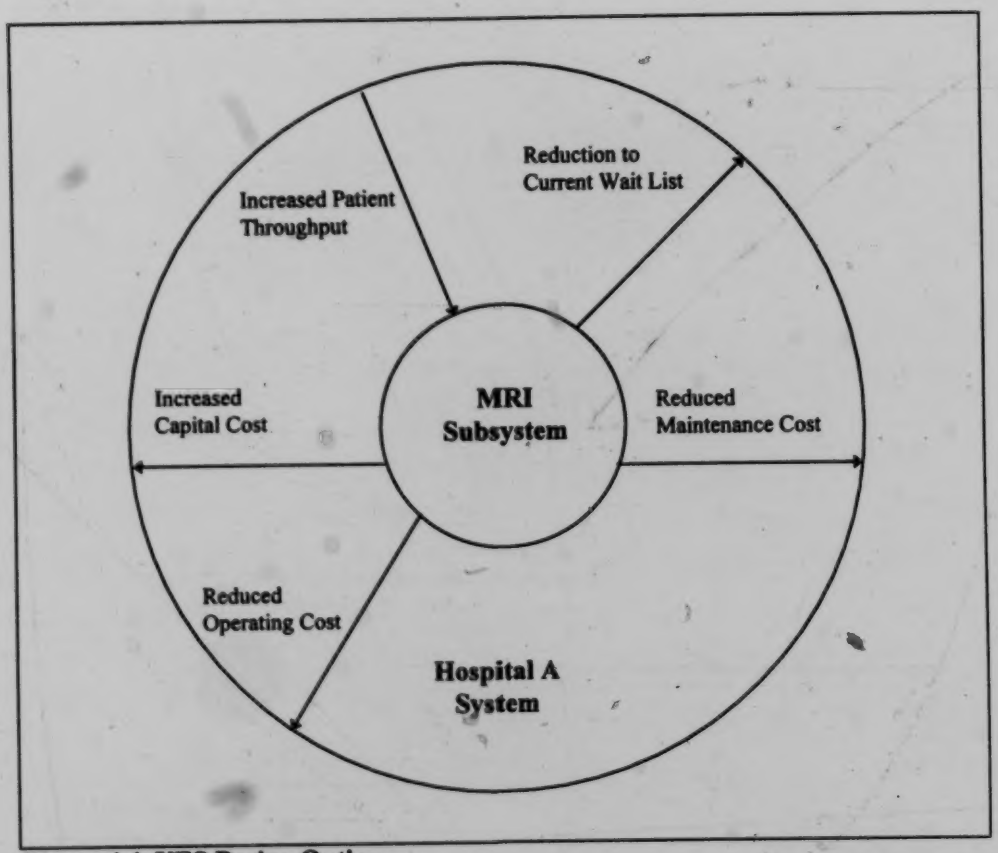


Figure 4.4 UES Design Option

As a far as resources are concerned, Hospital A would have to commit an amount denoted by *cf* from its capital fund towards recapitalizing the MRI subsystem. It is estimated that 70 percent of the capital funding, *cf*, would be directed towards upgrading the MRI's hardware and software components [HRA, 1995]. The remaining 30 percent would be allocated to performing necessary renovations to the existing facility. It is estimated that an operating expense *of*, would be required to fund operations which require increases of labor and supplies, about 75 percent and 25 percent, respectively [HRA, 1995]. Operating personnel is estimated to increase from its existing level of p_1 to p_2 full-time equivalents (FTE).

4.4 Computed Axial Tomography (CAT) Option

The second design option is to use CAT scan equipment to combat the rising wait list for an MRI. In this option, it is assumed that computed axial tomography, otherwise known as a CAT scan, can provide sufficient diagnostic information so that further medical intervention can be initiated to assist in progressing patient care. In some instances, a CAT scan can reveal adequate information for the physician to prescribe a particular treatment [NCI, 1996; AHA, 1996; Seidel, et al., 1991]. On other occasions, the CAT scan cannot reveal sufficient detail of areas, such as those associated with soft tissues [HRA, 1995]. When this situation occurs, the choice is to forgo all other potential radiological diagnostic tests, and proceed directly to have an MRI, because it can provide the detailed diagnoses required by the physician.

With respect to option two, it is assumed that Hospital A acquires new CAT scan equipment to handle the projected workload of patients who are unable to receive an MRI exam. Currently, Hospital A performs a total of ct_1 CAT scans annually. Introducing an additional CAT scan would enable Hospital A to increase its operating hours from hr_1 to hr_2 hours per day. The result is that scans are expected to increase annually by ct_2, where the total target number of CAT scans is given by $ct = (ct_1 + ct_2)$. It is further assumed that approximately one half of these scans will not reveal sufficient information for physicians to make a definitive diagnosis. As a result, patients will be referred to the MRI department for an MRI exam.

From a cost perspective, it is clear that those patients, whose diagnosis is inconclusive after having a CAT scan, will incur an added cost to their total patient care by requiring an MRI exam. In other words, the total diagnostic cost for these patients includes the cost of a CAT scan, plus the added cost of an MRI exam. For example, if an estimated cost of a CAT scan is given by cs per scan, and c_2 per exam MRI, then the total cost is given by $tc = cs + c_2$, which occurs when a CAT scan patient is referred for an MRI exam. This added cost tc would be funded from Hospital A's operating budget, and becomes an

opportunity cost for not having sufficient capacity to deal with patient volumes pertaining to MRI exams. The internal and external influences for the CAT scan option is shown in Figure 4.5.

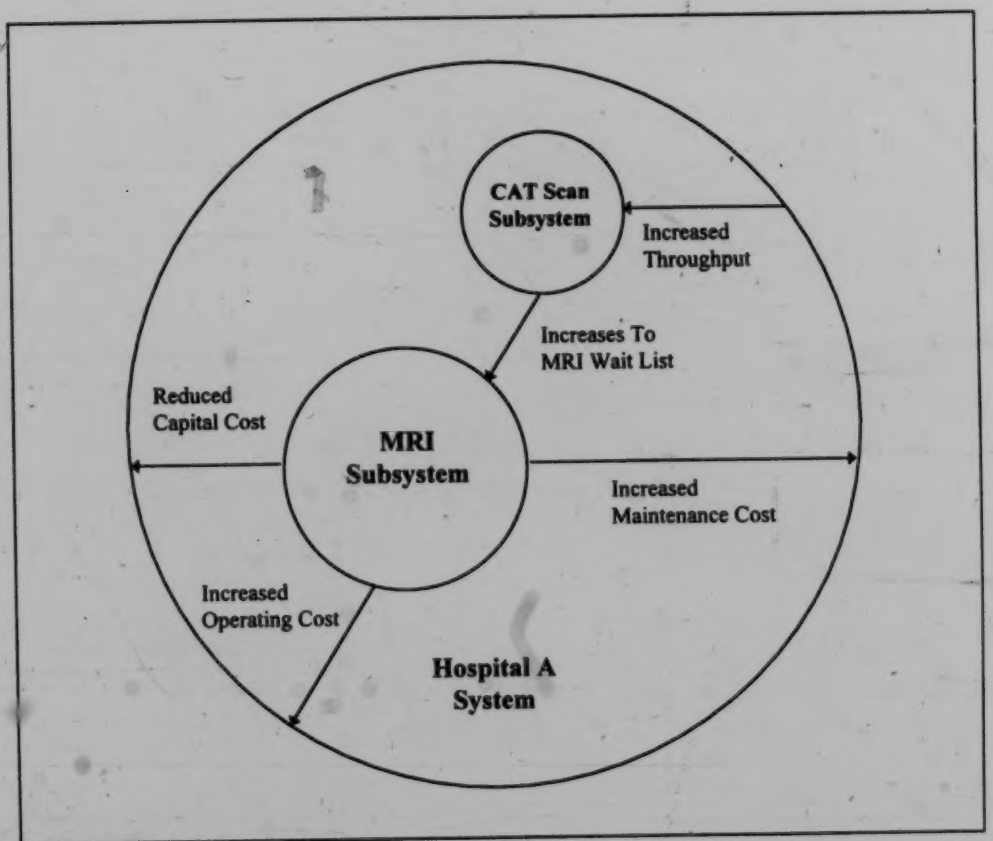


Figure 4.5 CAT Scan Option

Figure 4.5 illustrates the interaction between the MRI and the CAT scan subsystems, and their effect as a whole, on the Hospital A's system. Capital cost is reduced, because the CAT scan system requires no upgrading; however, maintenance cost is increased because of aging equipment. Also, operating cost for the MRI is expected to rise, largely due to equipment obsolescence. Altogether, all three cost elements impact the Hospital A's system. Capital cost is the only element which does not adversely affect Hospital A's

system. Unfortunately, it is reasonable to expect that any savings will be offset by increases in both maintenance and operating costs.

The CAT scan subsystem experiences an increase in patient workload, which is due in part to physician referral patterns. It is assumed that physicians are bypassing the MRI subsystem, because of its lengthy wait list. Physicians perceive that a CAT scan can provide sufficient diagnostic information to advance treatment for the patient. While a CAT scan can provide meaningful diagnostic information, there is a strong possibility that a number of scans will provide inconclusive information. When this occurs, the patient is referred to the MRI department for an MRI exam which results in an increase to the existing MRI wait list. This concept is graphically illustrated by an arrow extending from the CAT scan subsystem to the MRI subsystem in Figure 4.5.

4.5 Contract Another Region (CAR) Option

In design option three (CAR), a nearby health region in the province denoted as Health Region B is contracted to perform MRI exams on Hospital A's patients awaiting MRI exams. The total number of exams conducted by Health Region B is Q_B+q_2, where Q_B is the existing number of exams and q_2 is the quantity sent by Hospital A. Health Region B is expected to charge a rate bc per MRI exam; however, there are other accompanying costs which are incurred, such as transportation, accommodations, and meals, by sending Hospital A's patients to the Health Region B. These charges per MRI exam are denoted by ac. In total, an MRI performed at Health Region B per patient is simply the sum of $(bc + ac)$.

Patients sent to Health Region B are transported by a chartered bus which seats approximately 40 passengers. Approximately 21 hours are required to completely scan all 40 patients. Once all of the patients have been scanned, they are expected to return the next day accompanied with their MRI results. It is estimated that 15 round trips would be required per month to achieve Hospital A's annual target, Q. The interactions between Hospital A and the Health Region B are illustrated in Figure 4.6.

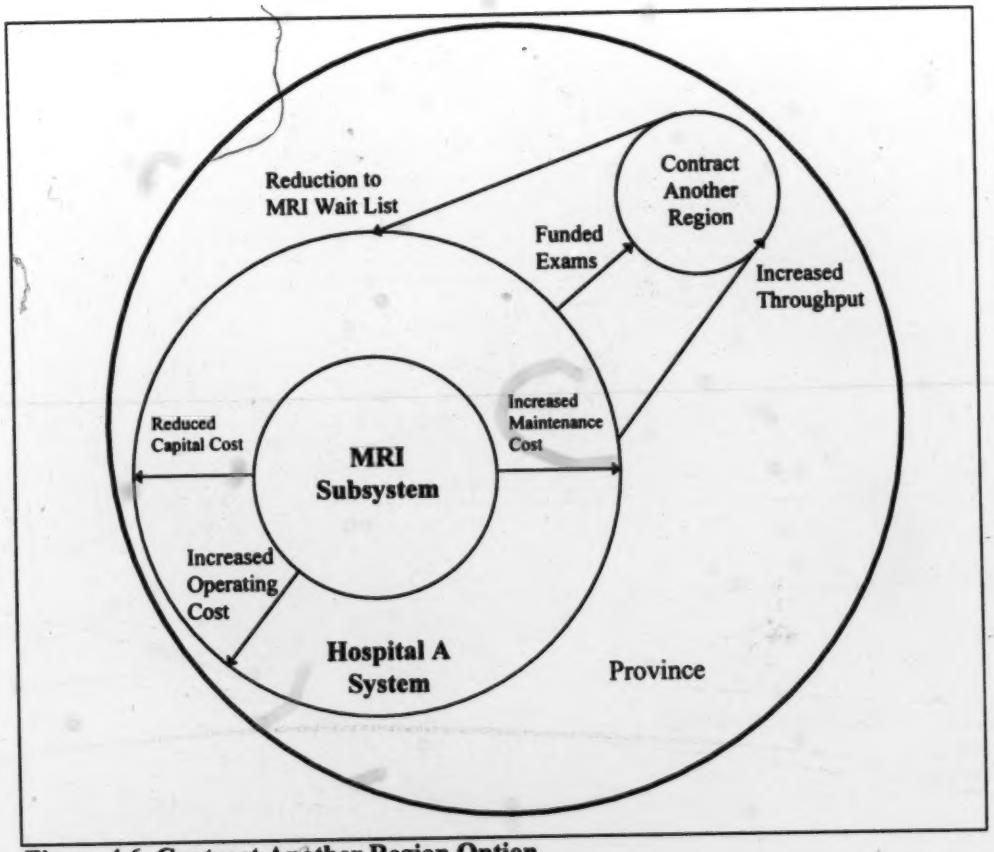


Figure 4.6 Contract Another Region Option

In Figure 4.6, it can be seen that Health Region B experiences an increase in throughput which is funded by Hospital A in an attempt to manage its MRI wait list. The result is a decrease in Hospital A's MRI wait list. Both operating and maintenance costs adversely impact Hospital A's operating budget due to the aging MRI equipment. With this option, Hospital A reduces its capital expenditures, but hospital managers must pay careful attention to rising operating and maintenance costs due to depreciation and obsolescence. Otherwise, there is a good possibility of running an operating deficit in the MRI department. In general, funding operating deficits usually implies that a number of hospital departments will have their budgets trimmed by the shortfall experienced in the over-cost department.

4.6 Contract Private Operator (CPO) Option

The fourth design option is to contract a private operator (CPO) to perform the remaining MRI exams to reach the defined target. The private operator and the hospital enters into an agreement whereby the private operator will perform a fixed number monthly of exams, *fe*, at a fixed price, *fp*. Any number of exams exceeding the fixed number per month qualifies for a reduction in price per exam to Hospital A. It is assumed that the private operator would upgrade its existing MRI system to handle the increased capacity, and also ensure that it has the necessary capability to perform detailed scans to specific parts of the body. Figure 4.7 illustrates the interaction between Hospital A and the private MRI operator.

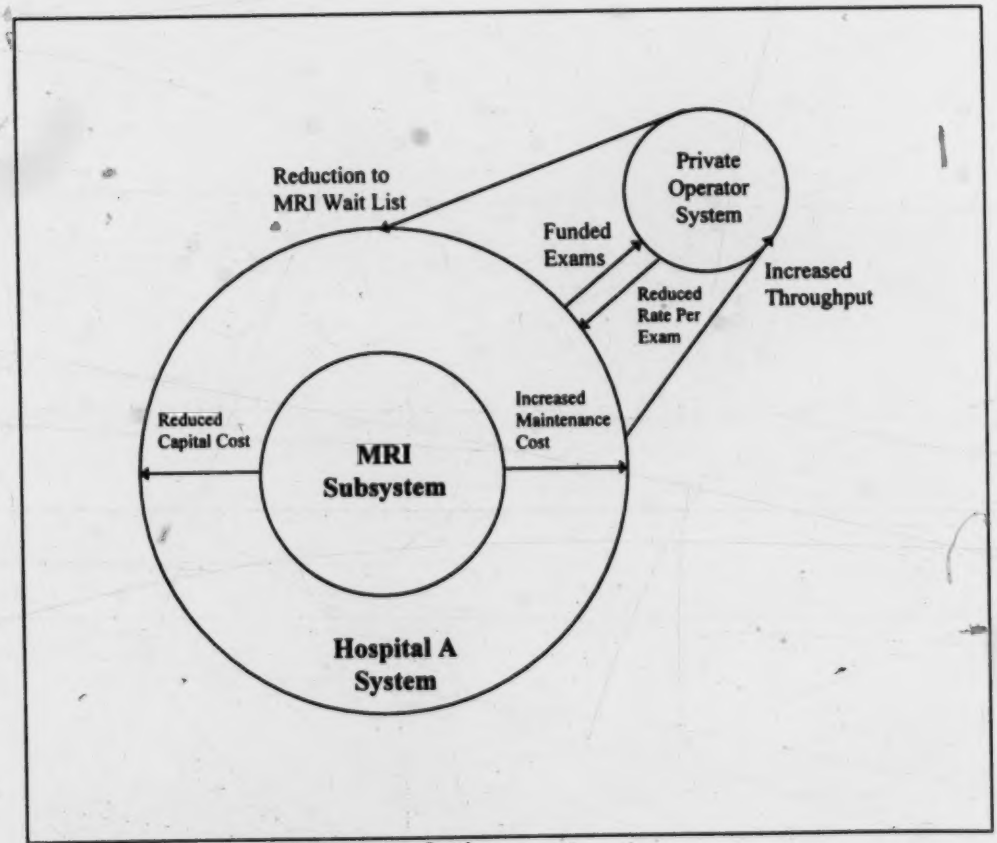


Figure 4.7 The Private Operator Option

Thus, the private operator is expected to supplement Hospital A's MRI operation by performing the total number of exams required to reach the target value for the health region, which is simply the difference between the target value and Hospital A's annual throughput. For instance, in this study, the private operator agrees to perform a total of $q_2 = (Q - q_1)$ exams. One-half of these exams are assumed to be fixed for the year, are assessed at a rate, *pc*, per exam. The other half have a reduced rate, *rc*, per exam as an incentive to Hospital A to provide future referrals.

In Figure 4.7, the use of the private operator system results in a reduction of Hospital A's capital costs, because no capital is invested to upgrade the MRI hardware and software components. Hospital A's operating budget will, however, be impacted by higher operating costs as a result of equipment obsolescence, and the cost of exams performed by the private operator. The private operator's system experiences an increase in throughput which is funded by Hospital A. As a result of this contract, the current wait list is expected to reduce significantly to cause improvement in the quality of delivered services.

4.7 Lease Capital Equipment (LCE) Option

The fifth option is to lease capital equipment (LCE) to perform the remaining MRI exams. This option requires that Hospital A lease a new MRI equipment, instead of pursuing any form of upgrades to the existing subsystem. The unit operating cost data is extrapolated from Hospital A's financial and operating databases. Hospital A will encounter lower maintenance and operating costs by leasing a new MRI equipment. The lease contract is for a period of five years, at which point the lessee returns the leased equipment. The estimated cost for the leased equipment is per month is *lc*. Hospital A would be responsible for maintenance costs. The relationship between Hospital A and its MRI subsystem with the lease option is illustrated in Figure 4.8.

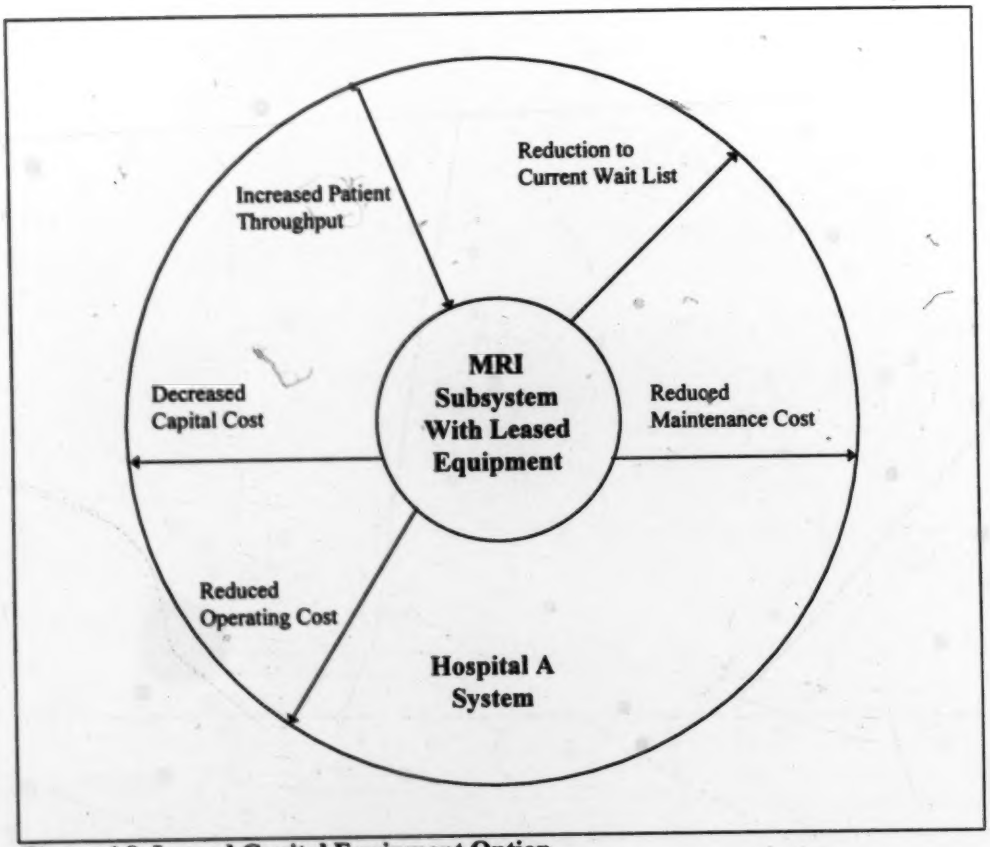


Figure 4.8 Leased Capital Equipment Option

Hospital A is expected to provide increased operating funding denoted by *of* to support increases in labor and supplies. The analysis is similar to option one (UES), except that Hospital A does not have to incur any additional capital cost. The lease payments are integrated with the rest of the operating costs. Hospital A is likely to benefit from leasing new state-of-the-art MRI equipment. These benefits are in the form of lower operating and maintenance costs as indicated in Figure 4.8. With increased capacity and current technology, Hospital A can increase throughput from the MRI subsystem. Overall, an increase in capacity implies a reduction to the current wait list, because of state-of-the-art technology associated with the leased MRI.

4.8 Contract Another Hospital (CAH) Option

The sixth option is to employ Hospital B in the same health region to conduct MRI exams. A proposal [HRA, 1995] is submitted to request the installation of a new MRI located at Hospital B. Essentially, Hospital B would provide MRI services to its patients, rather than sending them to Hospital A, as well as accepting cases from Hospital A. Hospital B is required to provide a throughput of q_2 exams annually to reach the target, Q, needed for Health Region A. In this case, Hospital B's operation is funded not by Hospital A, but rather by the Provincial Health Funding Agency.

Both capital and operating combined funding is denoted by *pf*. Capital equipment represents 85 percent of *pf*, while operations account for the remaining 15 percent of *pf* [HRA, 1995]. It is assumed that Hospital B's MRI operation has a similar cost structure as compared to Hospital A. Figure 4.7 illustrates the interaction between Hospitals A and B, along with the Provincial Health Funding Agency.

From Figure 4.7, it can be seen that the capital cost is reduced for Hospital A's MRI subsystem by not pursuing any upgrades. However, it is anticipated that the upgrade cost would be negated by Hospital B's capital purchase request for an MRI unit. The Provincial Funding Agency is primarily responsible for distributing operating and capital funds. As a result, it would be funding the MRI operation at Hospital B. It is expected that Hospital B would have to perform a total of q_2 MRI exams annually. This is the required number of exams necessary to satisfy the target for Health Region A. In other words, the MRI operations at Hospital A and B would collectively provide a total of Q exams annually.

The effect of introducing a second MRI into Health Region A serves to reduce the impact of the existing wait list. In fact, Hospital A can direct a number of its patients to Hospital B, if it cannot cope with existing levels. In other words, Hospital A can elect to process patients quicker by simply referring them to Hospital B.

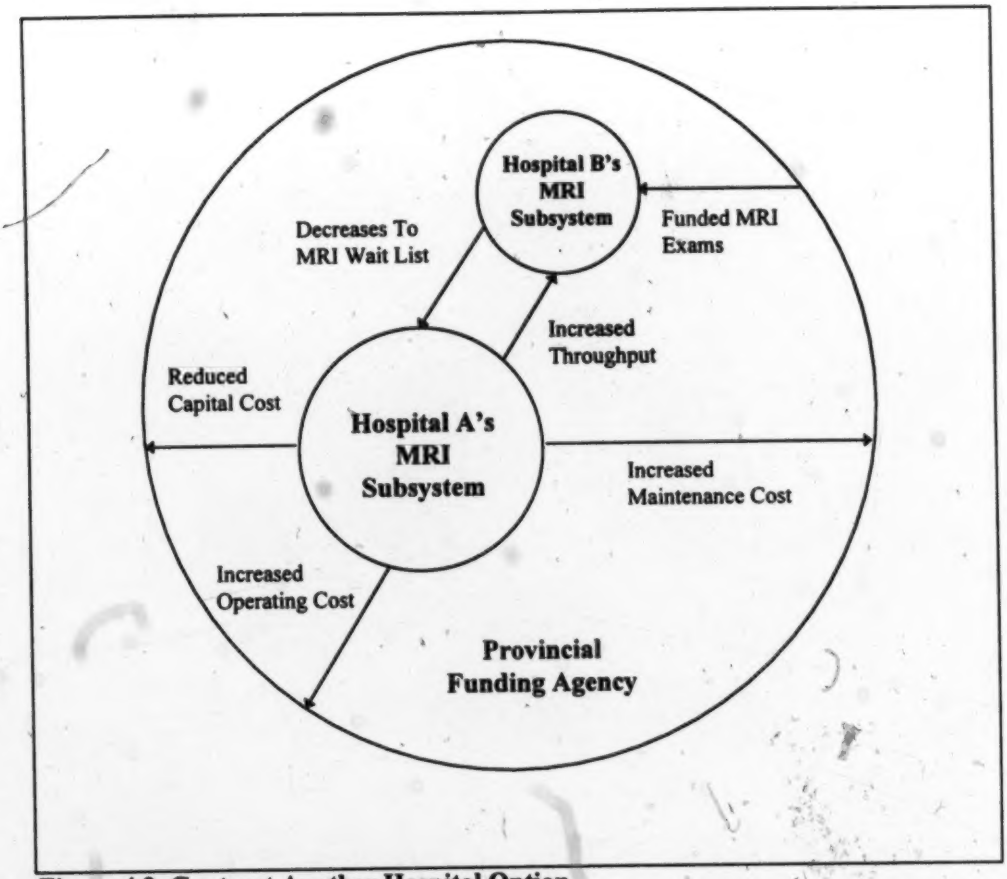


Figure 4.9 Contract Another Hospital Option

Unfortunately, Hospital A cannot ignore increasing maintenance and operating costs for its existing MRI operation. The MRI department at Hospital A must adjust its annual budget to reflect these increases to operating and maintenance costs. These costs are expected to be absorbed by the Provincial Funding Agency when they distribute operating grants for the following fiscal year.

4.9 Contract Mobile Operator (CMO) Option

The seventh and last design option is to contract with a mobile operator (CMO) who provides MRI exams. This option entails having a mobile unit on site at Hospital A, where it would provide MRI exams on the spot with results following shortly. The effect

is that Hospital A can utilize this option to alleviate a backlog of patients currently found on its wait list. The mobile operator is expected to perform a total of q_2 exams annually.

Figure 4.8 illustrates the interaction between Hospital A and the mobile operator. It is anticipated that the mobile operation would be utilized once a month, and operate for a total of d_2 days. The estimated rate per exam, mr, accounts for the utility costs incurred at Hospital A's site. Figure 4.8 illustrates the interaction between Hospital A and the mobile operator.

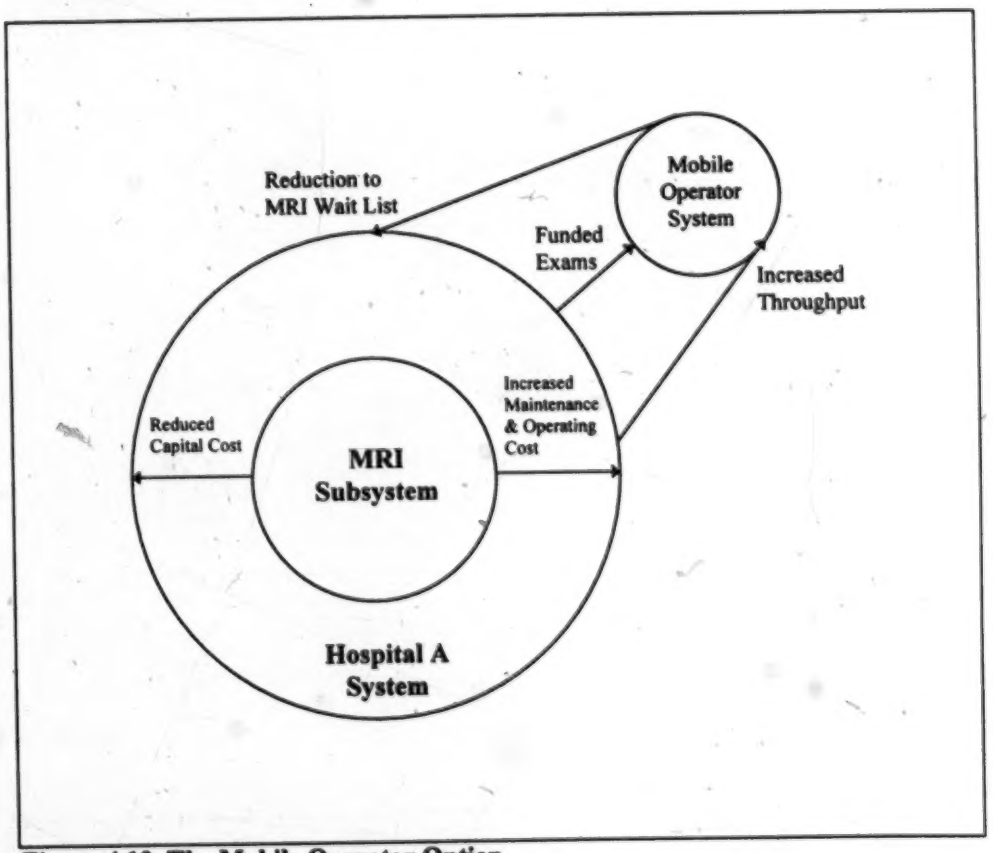


Figure 4.10 The Mobile Operator Option

Again, Hospital A experiences increased maintenance and operating costs from the MRI subsystem due to equipment obsolescence, while it expects a reduction in capital

expenditures, because it is not incurring any capital costs. Exams are funded from Hospital A's operating grant. An increase in throughput is shown for the mobile operator, while a reduction in the wait list is experienced by Hospital A.

CHAPTER 5
COMPUTER MODELING AND EXPERIMENTAL ANALYSIS

In this chapter, the author discusses aspects pertaining to computer modeling and experimental design analyses. Computer modeling is an integral element in the development of the stochastic capital budgeting model. The complex mathematical equations derived in Chapter 3.0 are translated into computer models to facilitate the analyses. Computer modeling includes the VARSIM and the stochastic models of Hospital A's capital budgeting problem. The experimental analysis includes a discussion of the design options matrix, as well as the required data for validation, the number of iterations in a simulation run, and the experimental setup and experimentation.

5.1 Flowcharts of Computer Models

The VARSIM and the stochastic computer models are employed to solve Hospital A's magnetic resonance imaging (MRI) problem. The VARSIM model identifies sensitive variables in the annual equivalent cost (AEC) function which are used as input in the stochastic models. Each sensitive random variable is described by an appropriate probability distribution function using the Bestfit program and sample data [Palisade, 1995]. Random samples are drawn from these distribution functions in the stochastic model to estimate an expected AEC for the MRI design options. Flowcharts depicting the algorithm for the VARSIM and the stochastic models are discussed in the next section.

5.1.1 VARSIM Flowchart Model

The sensitivity model is carried out using the VARSIM program which is comprised of a general library of routines used to evaluate the sensitive random variables in the AEC function [Griffin, 1995]. VARSIM identifies, specifically, those random variables which contribute towards the total variance of the AEC function. Figure 5.1 illustrates how the AEC function interacts with the VARSIM library of routines.

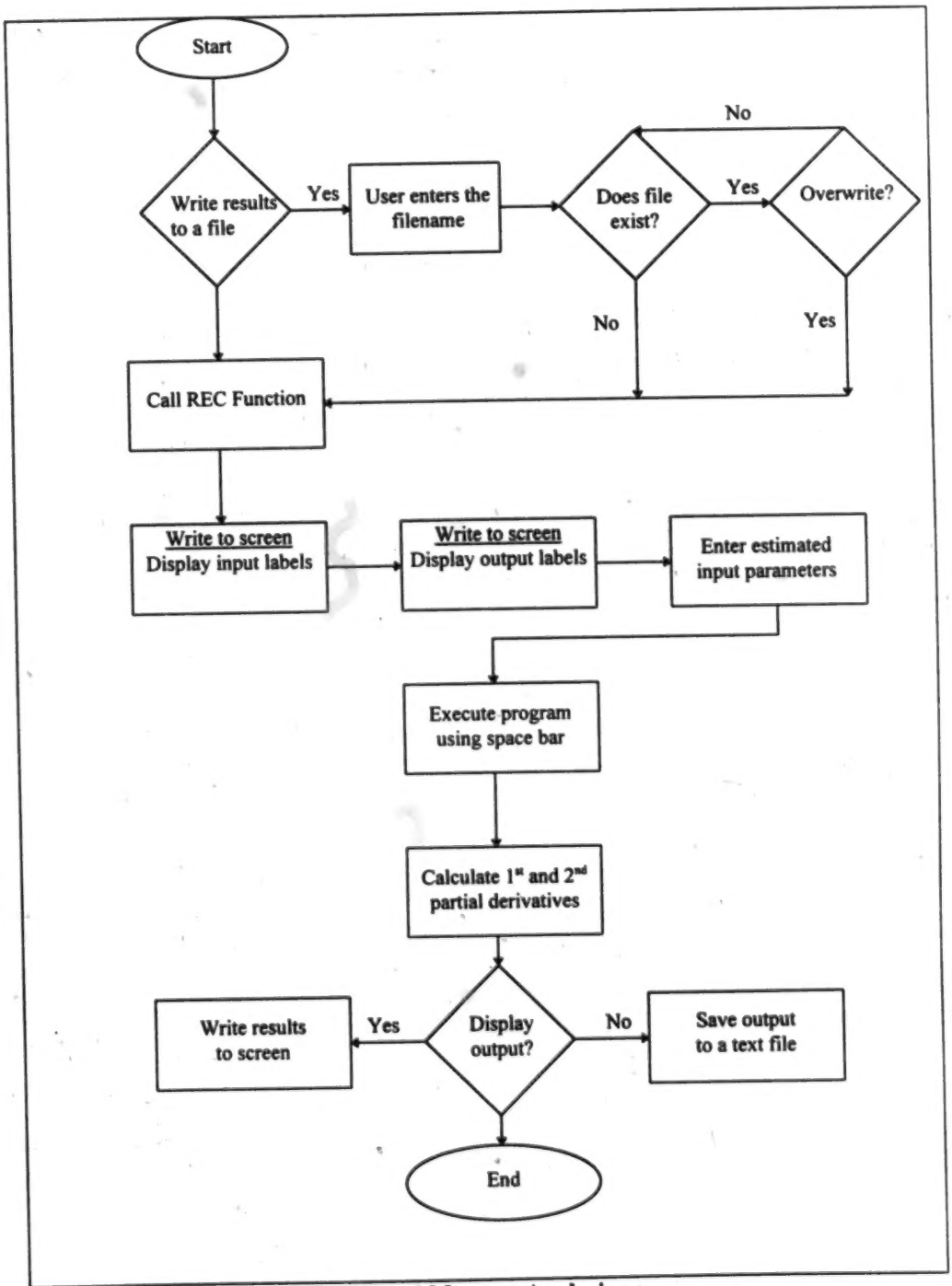


Figure 5.1 Flowchart For Functional Moment Analysis

VARSIM is a DOS-based program which provides an interactive screen for the user to enter data (i.e., mean and standard deviation) for each random variable. An input program file is written in FORTRAN and compiled using an MS FORTRAN compiler v.5.1 [Microsoft, 1995]. The FORTRAN program contains the input variables, labels, and REC function which is used to calculate the AEC value for an MRI exam. Once the program is compiled, its output is directed to the screen. The output shown includes the variables names, and column labels (i.e., %VAR, Std Deviation, %BIAS). Next, the user is required to enter the standard deviation for each random variable. After the input data are entered, the first and second partial derivatives of the AEC function are estimated with respect to each random variable, in order to estimate the numeric value of the expected value and variance of the AEC function.

The results from VARSIM are displayed to the screen for immediate interpretation. Alternatively, VARSIM results can be saved to a text file and imported in any document. However, some modifications to the text file must be made after importing into a report, because of problems related to formatting. It is important to note that the user can always make changes to any standard deviation entered incorrectly, prior to saving the results to a text file.

5.1.2 Flowchart of Stochastic Models

The stochastic computer modeling is carried out by incorporating two add-in programs to the Microsoft Excel version 7.0 spreadsheet program. These two add-in programs include: Bestfit and @Risk [Palisade, 1996]. These programs are all executed under the Microsoft Windows 95 operating system. The random variables identified by the VARSIM program are used as input to the Bestfit program. These random stochastic variables are selected on the basis of their contribution towards the total variance in the AEC function. Bestfit attempts to fit each sensitive random stochastic variable with a probability distribution function (PDF). The flowchart for Bestfit is shown in Figure 5.2.

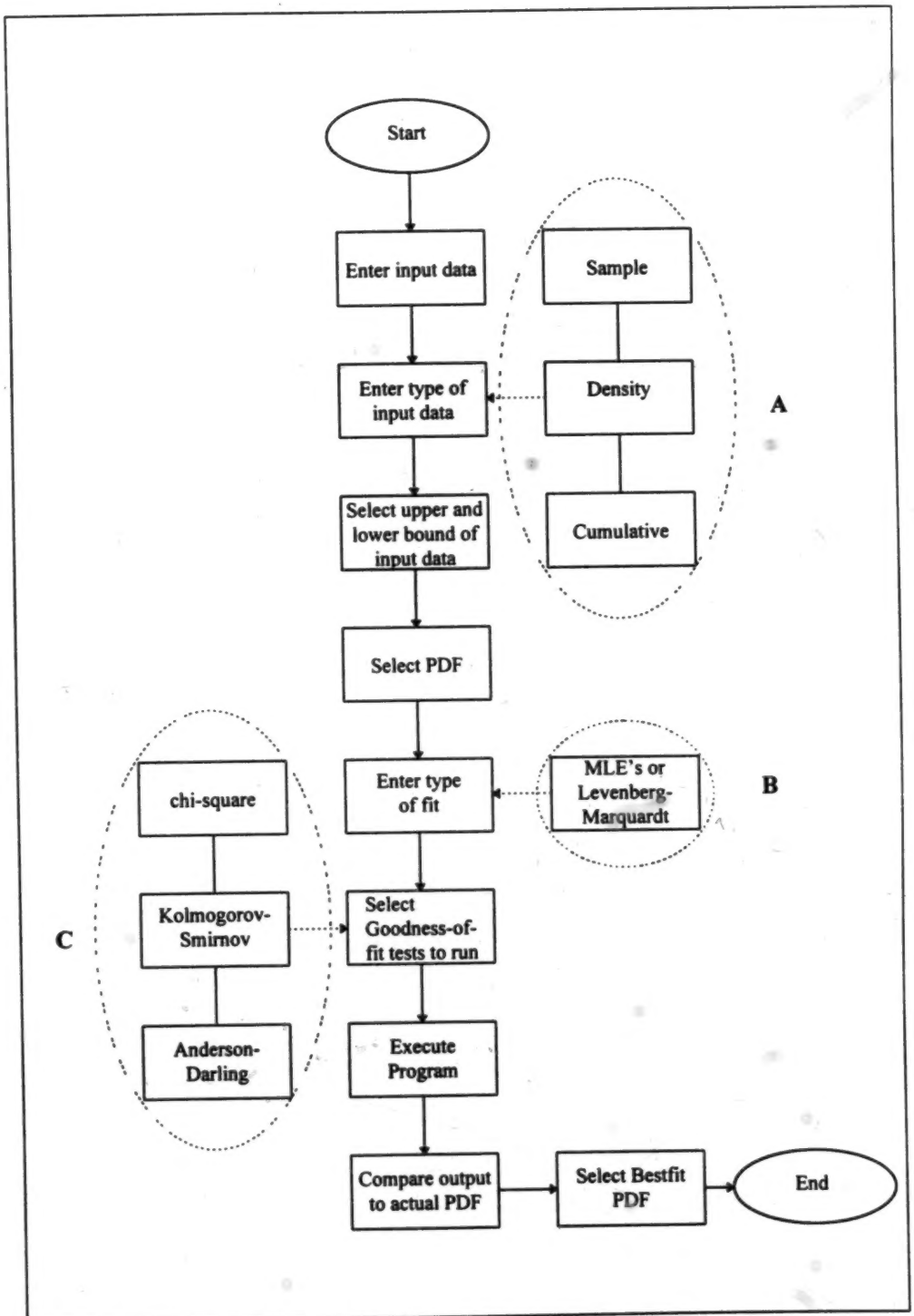


Figure 5.2 Flowchart Model For Fitting PDFs Using Bestfit.

Bestfit permits the user to enter three types of input data: sample, density, and cumulative denoted by the letter A in Figure 5.2. Data can be entered directly into Bestfit's input sheet, or it can be linked from an Excel worksheet. Figure 5.3 is a flowchart for processing input data types.

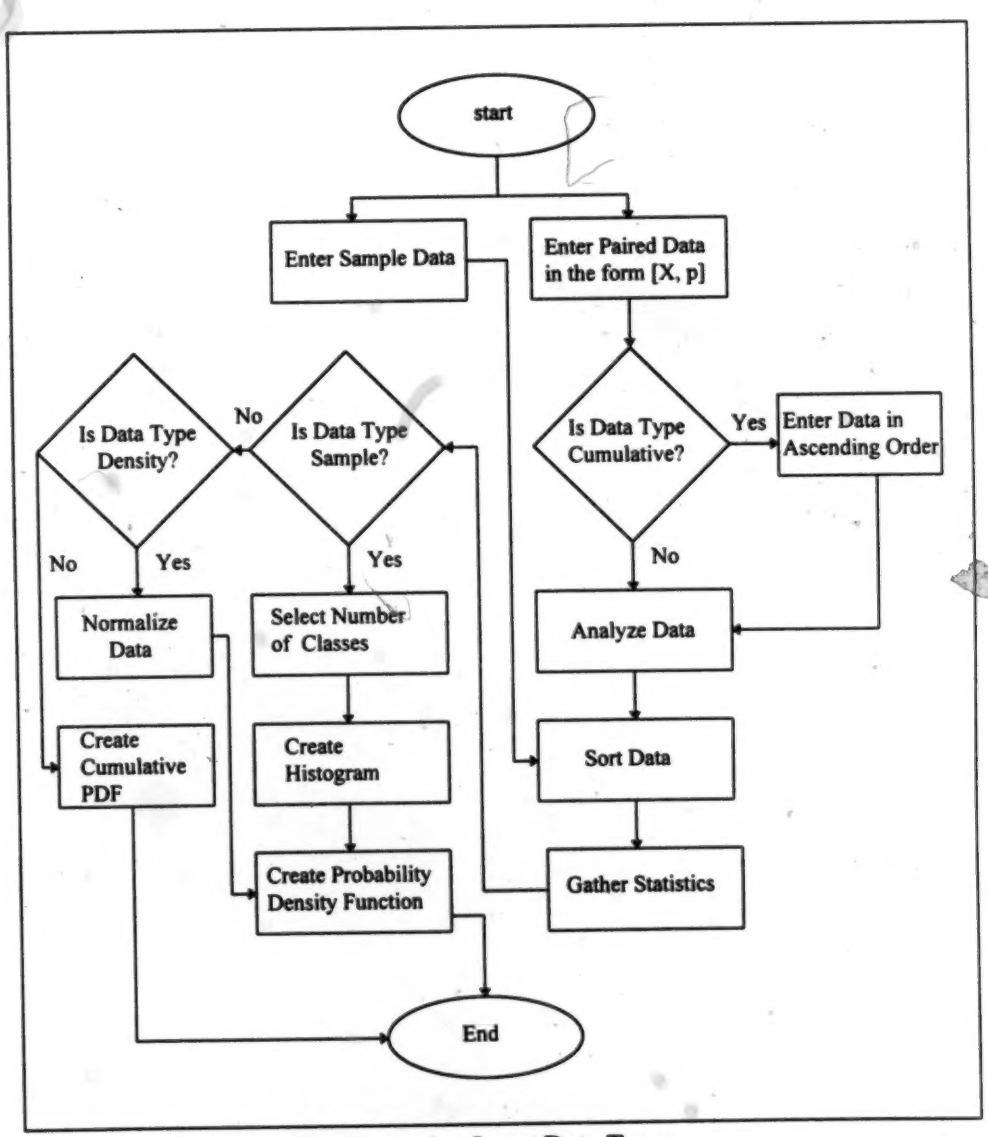


Figure 5.3: Flowchart For Processing Input Data Types.

Sample data is usually selected from a population. It is used to estimate properties of the population. Bestfit sorts the input data in ascending order, gathers basic statistics (i.e., mean, standard deviation, variance, etc.) and converts the data into a histogram to create a probability distribution function [Palisade, 1995].

Density input data is usually entered in the form of [X, p] pairs, where X is a value on the probability density curve which corresponds to a specific probability weight, p. Bestfit processes the density data, and proceeds to sort it in ascending order, and estimates basic statistics similar to those for the sample input data. The last step in the process entails normalizing the data to create a probability distribution function. It is important to note that a number of guidelines must be followed when inputting density data. The minimum X value must be less than the maximum X value, while each X input must be greater than, or equal to, the minimum X value; and less than, or equal to, the maximum X value. Furthermore, two X values cannot be the same. Lastly, the value of p must be greater than, or equal to, zero [Palisade, 1995].

Cumulative data is similar to density data in that both are in the form [X, p] pairs, where X is a value on the cumulative probability density curve which corresponds to a specific probability weight, p. There are a number of guidelines to follow when entering cumulative data. For instance, the minimum X value must be less than the maximum X value. Each X value must be greater than the minimum X value, and less than, or equal to the maximum X value. Two or more X values cannot be equal. With respect to p values, each p value must be greater than, or equal to, zero; and less than, or equal to, one. P values must be in increasing order when entering the [X, p] paired cumulative data. One last point to remember is that at least two data pairs must be entered in the spreadsheet. Once the cumulative data is entered in ascending order, statistics are gathered in a manner similar to that used for sample and density data. The final step is to create a cumulative probability distribution. A probability value of p on the cumulative probability distribution curve is the probability of obtaining a value that is less than, or equal to, the corresponding X value [Palisade, 1995].

A choice of 18 probability distribution functions (PDF) are offered by Bestfit, however, the most practical approach is to select all PDFs to minimize potential errors of omitting a representative PDF. In order to fit a distribution to the input data, Bestfit uses two methods: Maximum Likelihood Estimators (MLE) and Levenberg-Marquardt [Palisade, 1996]. The choice of a method depends largely on the integrity of the input data. An expansion of this step in the Bestfit process is circled and denoted by the letter B in Figure 5.2. The Maximum Likelihood Estimator methodology is illustrated in Figure 5.4.

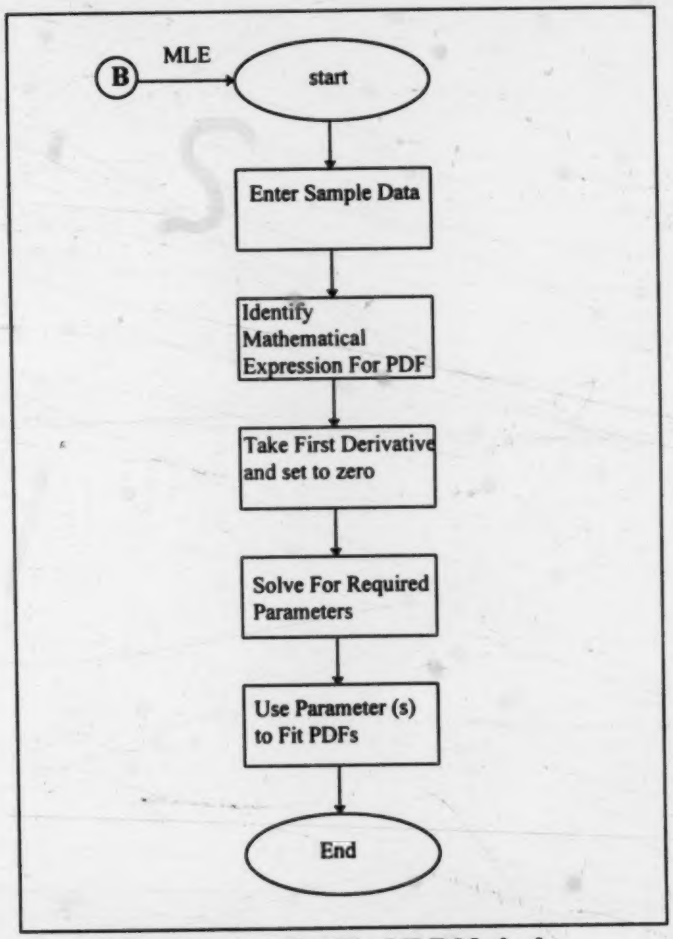


Figure 5.4: Flowchart For The MLE Method.

MLEs attempt to fit a distribution to the input data by determining initial guesses of parameters, such as the mean and standard deviation for a normal distribution. Estimates of these parameters are derived from the original input data which are subsequently used as the initial "best guess" parameters in the goodness-of-fit analysis. The MLE method is appropriate for input distributions that are very smooth. The MLE of a distribution is determined by maximizing the PDF with respect to the unknown parameter(s). This involves taking the first derivative with respect to the unknown parameter(s), and setting the expression to zero to solve for the unknown parameter(s).

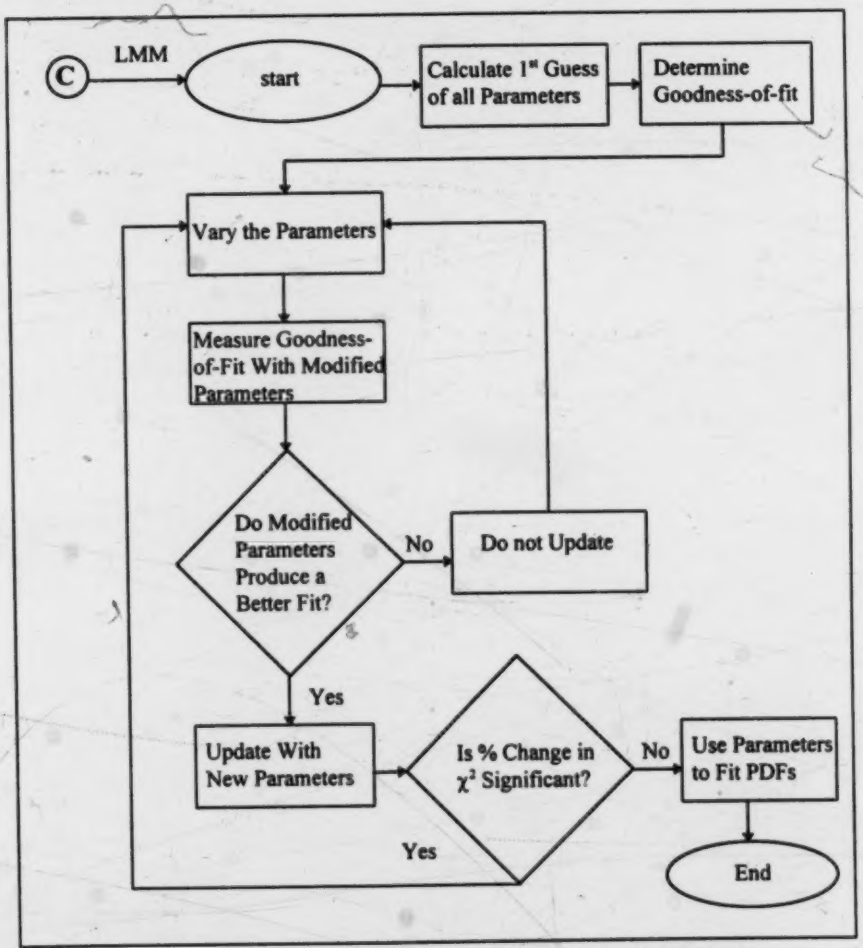


Figure 5.5: Flowchart For The Levenberg-Marquardt Method.

The second algorithm, called the Levenberg-Marquardt Method (LMM), is shown in Figure 5.5. The Levenberg-Marquardt algorithm is used to maximize the goodness-of-fit between input data and a distribution function. This method is generally used when the input distribution is incomplete, or not particularly smooth. Furthermore, only the chi-square test is used with this method, because it is the most frequently employed, and can be easily calculated. As shown in Figure 5.5, this method calculates the "first guess" of all parameters which are subsequently used to determine the goodness-of-fit of the input data. Next, the parameters are varied by a specified value. At this point, the goodness-of-fit is measured again using the modified parameters. If the modified parameters do not produce a better fit, then further update to these parameters are necessary. However, if the modified parameters are sufficient, then the next logical step is to calculate the percent change in the Chi-Square statistic to determine if the change in magnitude is significant. For example, if the percent change is greater than five percent, then the process must be repeated by varying the parameters in step three. Once the percent change in the chi-square statistic stabilizes, the parameters can be used to fit PDFs.

The three goodness-of-fit tests used in Bestfit include: Chi-Square, Kolmogorov-Smirnov and Anderson-Darling. These goodness-of-fit tests are circled in Figure 5.2, and are denoted by the letter C. Each goodness-of-fit test is expanded and described separately to illustrate the method by which each test statistic is calculated. A goodness-of-fit test statistic is used to test the hypothesis that a random variable has a specified theoretical statistical distribution [Pfaffenber and Patterson, 1987]. In this research, the null hypothesis, H_o, tests whether the input data is from a distribution function reported by Bestfit. If H_o is rejected, then the alternate hypothesis, H_a, is accepted. Accepting H_a implies that the input data is not from a distribution reported by Bestfit

The chi-square goodness-of-fit test is based on the difference between the frequencies in the classes of the observed sample and the expected class frequencies, if the random variable conformed to the assumed theoretical distribution [Pfaffenber and Patterson,

1987; Jobson, 1991]. Figure 5.6 illustrates the Chi-Square process for testing the null hypothesis.

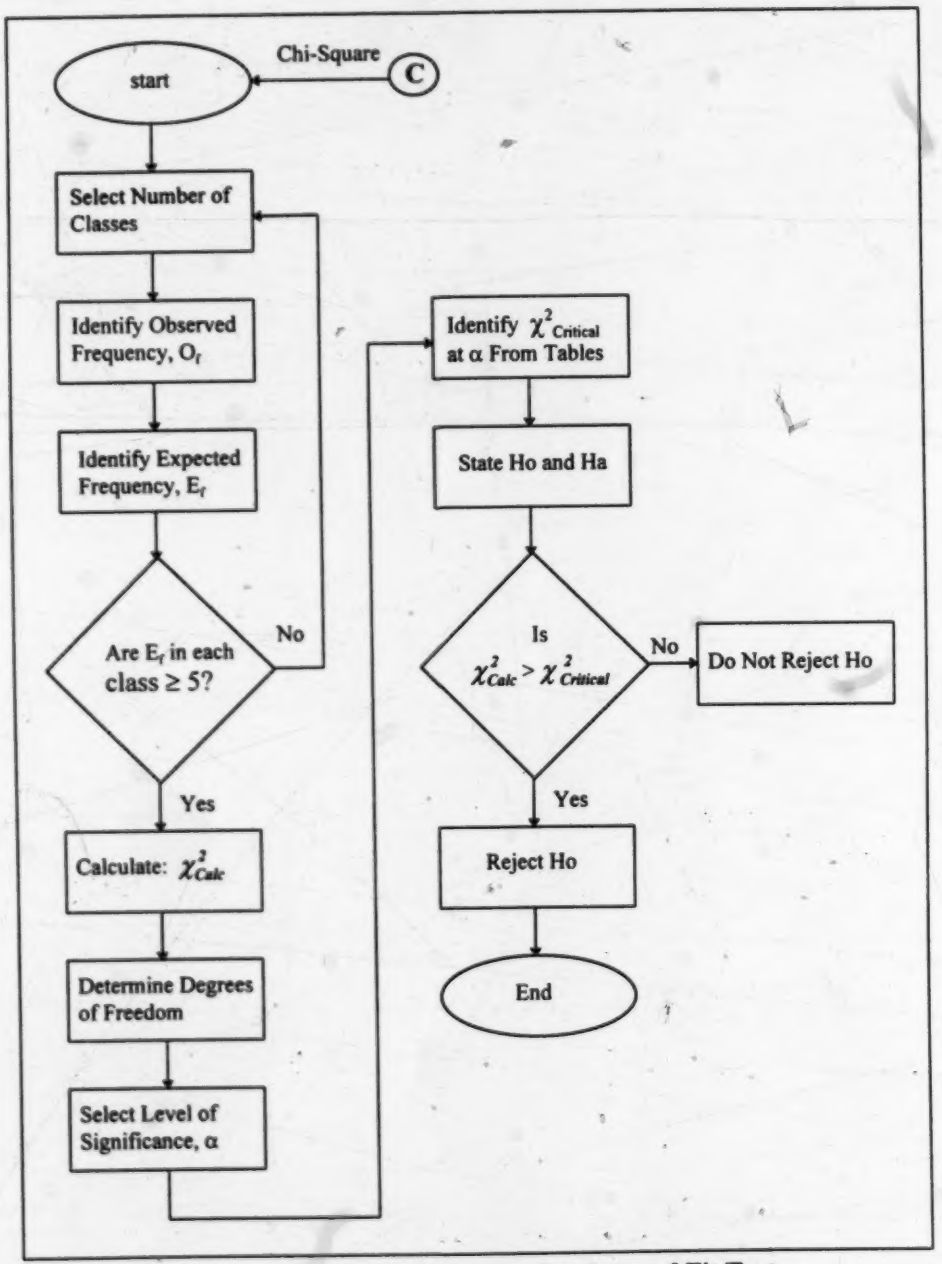


Figure 5.6: Flowchart For The Chi-Square Goodness-of-Fit Test.

The first step in the process requires that a suitable number of classes are determined such that the observed and expected observations can be grouped appropriately. If the expected frequency of observations is less than five, then it is necessary to reduce the number of classes. The χ^2_{Calc} statistic is calculated by summing the ratio of the difference between the observed and expected values squared divided by the expected value across all classes. Next, one determines the degrees of freedom and the level of significance. In this research, the level of significance used in all three goodness-of-fit tests is $\alpha = 0.05$. The $\chi^2_{Critical}$ value at the five percent level of significance is determined by using tables of calculated Chi-Square values at different levels of significance [Pfaffenber and Patterson, 1987; Miller and Freund, 1985]. The χ^2_{Calc} result is compared to the $\chi^2_{Critical}$ value, with the null hypothesis rejected if $\chi^2_{Calc} > \chi^2_{Critical}$, thereby leading to the conclusion that the Bestfit probability distribution function is not a good fit. A weakness of the chi-square test is that no clear guidelines are provided to select the number of classes (intervals).

The Kolmogorov-Smirnov (K-S) test can be used for any hypothesized, continuous, cumulative distribution function. The K-S test is widely used to test for normality, and does not depend on the number of classes, which makes it more advantageous than the Chi-Square test. One weakness of the K-S test is its inability to detect tail discrepancies [Palisade, 1995]. The first step in the K-S test is to determine if the distribution of sample data is continuous. If it is not continuous, then the Chi-Square test must be used. Alternatively, if the distribution is continuous, then Bestfit proceeds to calculate the sample data mean and standard deviation. These two parameters are used to calculate a modified test statistic, t_m, which is compared to the critical K-S test statistic, t_c, at the five percent level of significance. The value calculated for t_m is based on the largest difference in absolute value between the observed and the hypothesized distribution functions. The value for t_c is determined by using tables [Pfaffenber and Patterson, 1987; Miller and Freund, 1985]. If $t_m > t_c$, then the null hypothesis is rejected, leading to the conclusion that the probability distribution reported by Bestfit does not fit the sample data. Figure 5.7 illustrates the K-S goodness-of-fit flowchart.

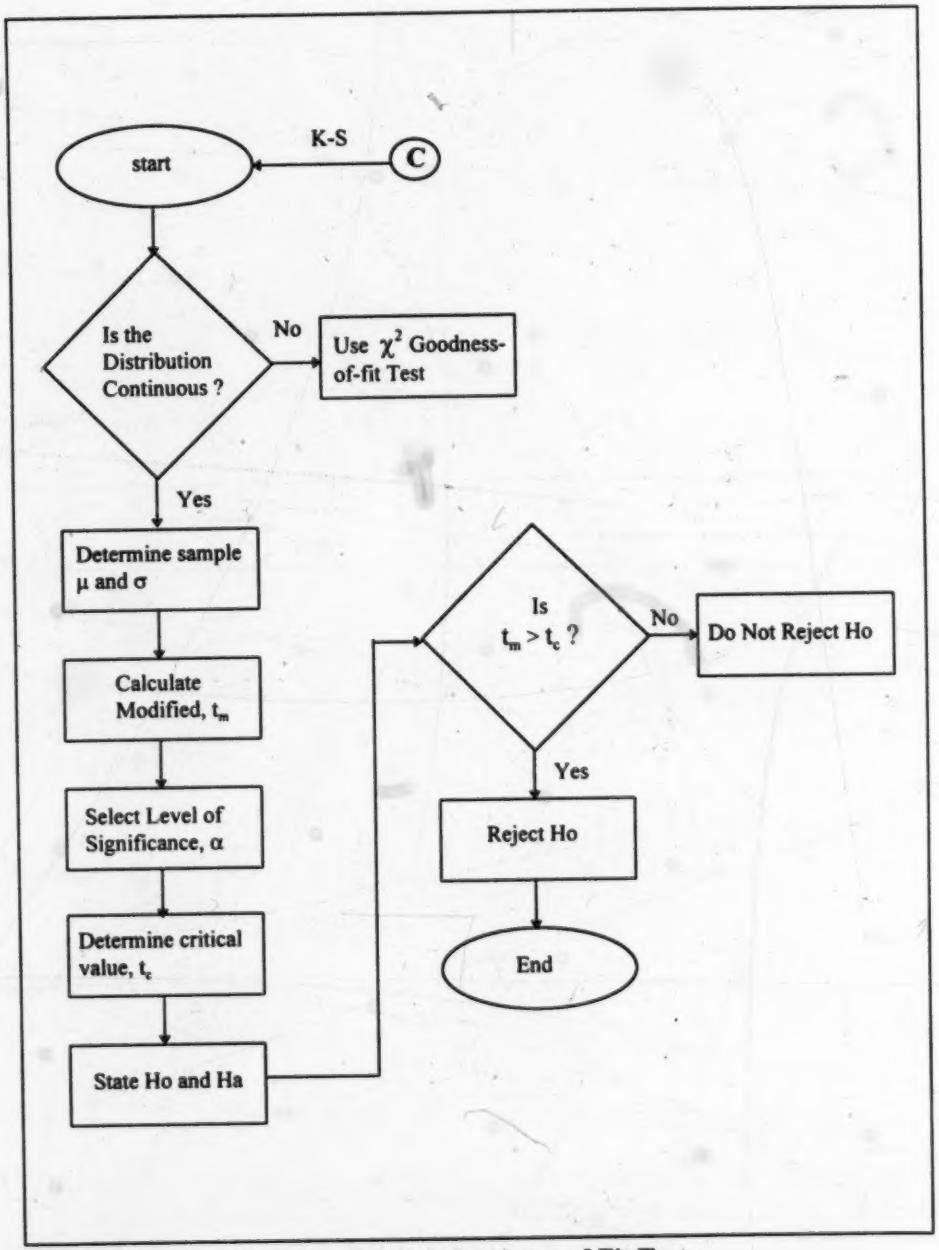


Figure 5.7: Flowchart For The K-S Goodness-of-Fit Test.

The Anderson-Darling (A-D) test is similar to the K-S test, except that more emphasis is placed on the tail values. Also, it does not depend on the number of classes selected for the test analysis. A weakness of the A-D test is that it can only be used with sample data, whereas, both the chi-square and the K-S tests can be used with any of the three input data types (sample, density, cumulative). Figure 5.8 illustrates the flowchart for the A-D goodness-of-fit test

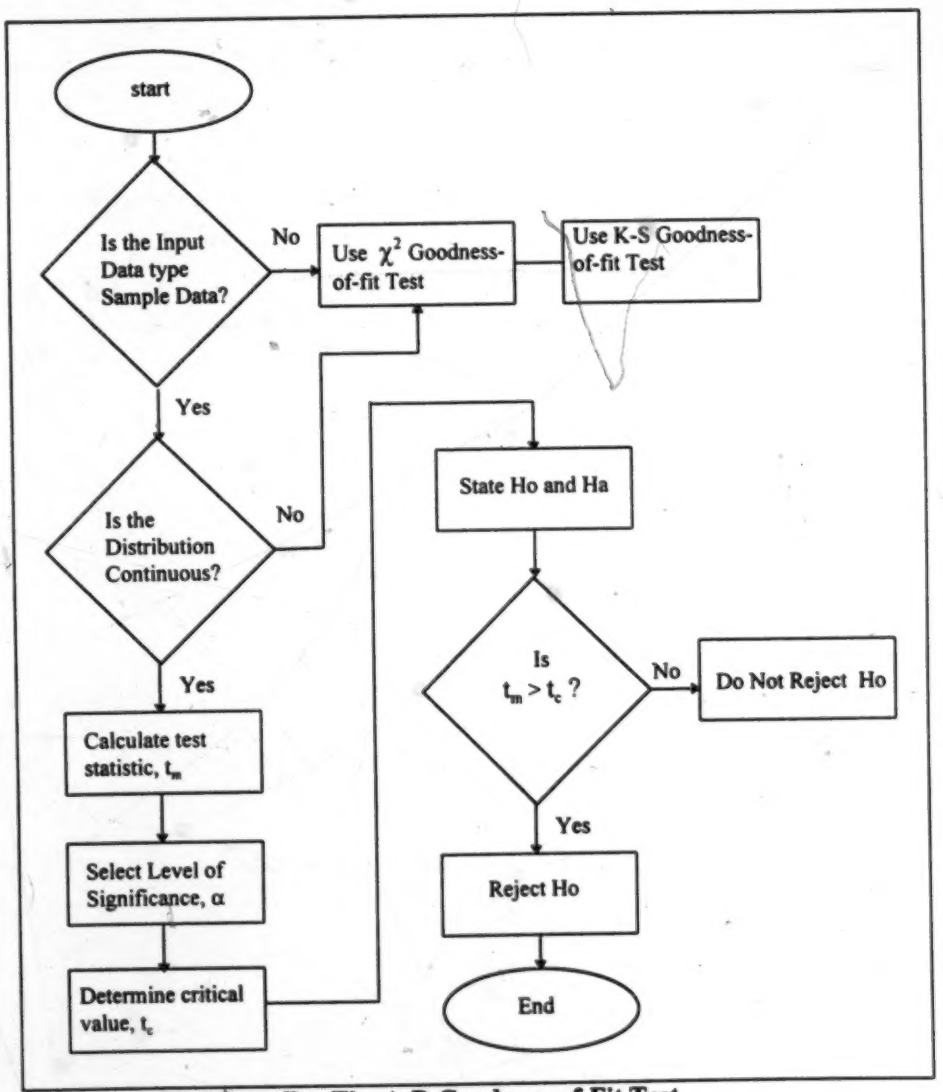


Figure 5.8: Flowchart For The A-D Goodness-of-Fit Test.

The choice among goodness-of-fit tests depends on the critical value chosen for the test. The critical value separates the rejection region from the acceptance region. In other words, the critical value determines whether a fitted distribution should be accepted or rejected for a random stochastic variable. The critical value is dependent on the type of fitted distribution, the sample size, and the level of confidence defined by α. For instance, selecting a small level of confidence, α, decreases the probability of accepting the Bestfit result when it is not the distribution that created the input data set [Palisade, 1995]. The results from the Bestfit analysis include the smallest value of α that passes the null hypothesis test, H_o, and a number of critical values for selected values of α.

Apart from examining goodness-of-fit tests, other considerations must be taken into account when selecting an appropriate PDF. For instance, it is essential to compare the fitted distribution's descriptive statistics, such as the mean, median, standard deviation, variance, skewness, and kurtosis, against those from the original input data. Also, the choice of a fitted-distribution depends on the ease of estimating unknown parameters. For example, a sample mean for a normal distribution can be estimated more easily than parameters for a beta distribution. Once the fitted distributions from Bestfit are selected, they are subsequently coded and entered into the stochastic model developed in the Excel spreadsheet. @Risk is used to carry out the Monte Carlo simulation of the stochastic model of the AER function which forms the basis of this research. Figure 5.9 illustrates the flowchart model for risk simulation using @Risk.

The selected Bestfit PDFs for the uncertain random variables are entered into the stochastic capital budget model in the @Risk environment. The setup of the simulation model entails the selection of sampling type, standard recalculation, and outputs and entering a random seed which is illustrated by letter D, E, F. The outputs of the function in the spreadsheet can be calculated using the expected value, Monte Carlo, and the true expected value. The expected value recalculation method causes the distribution functions to return their expected mean each time Excel undertakes a recalculation. Figure 5.10 illustrates the flowchart for the simulation model recalculation methods.

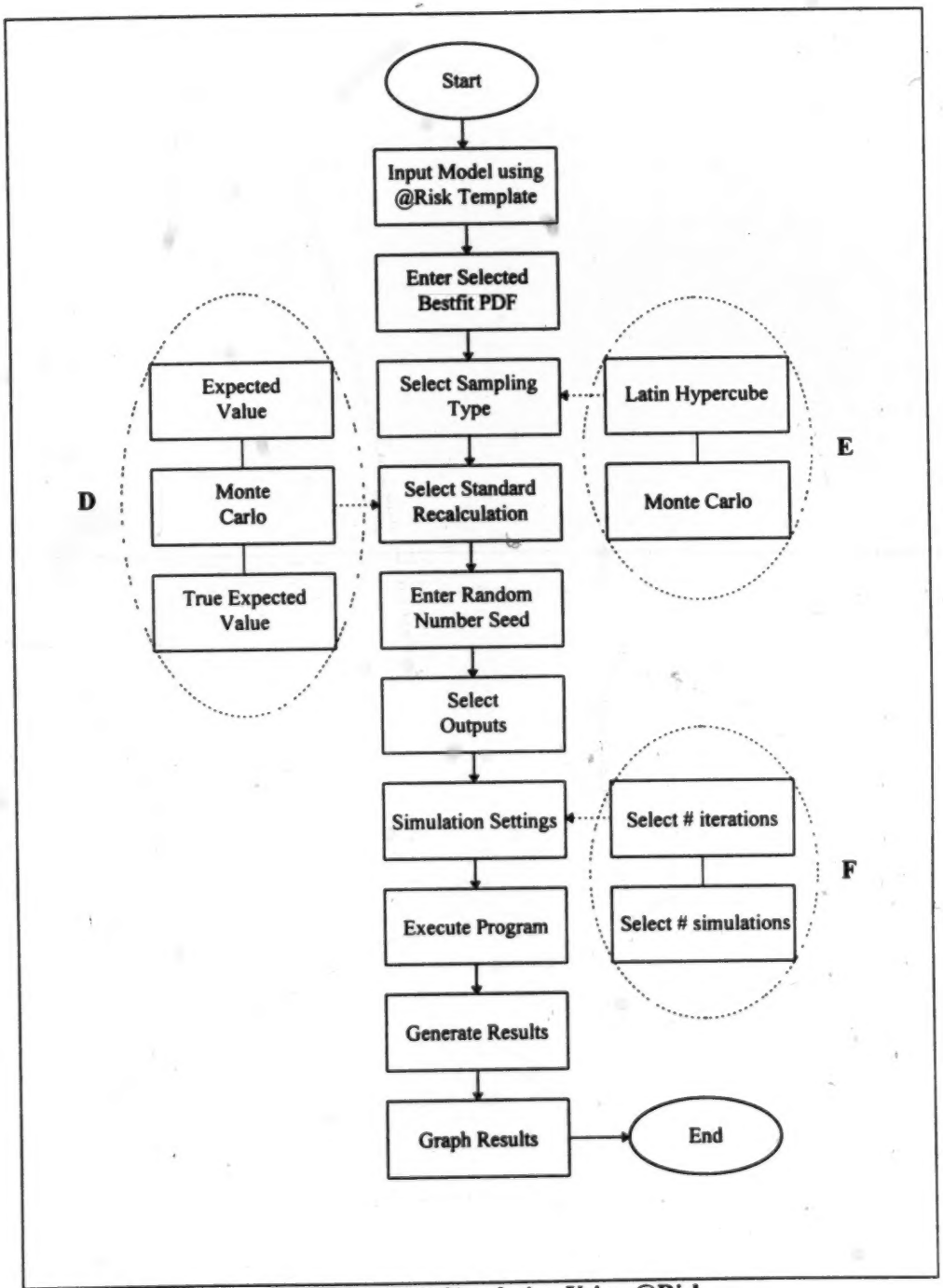


Figure 5.9 Flowchart Model For Risk Simulation Using @Risk

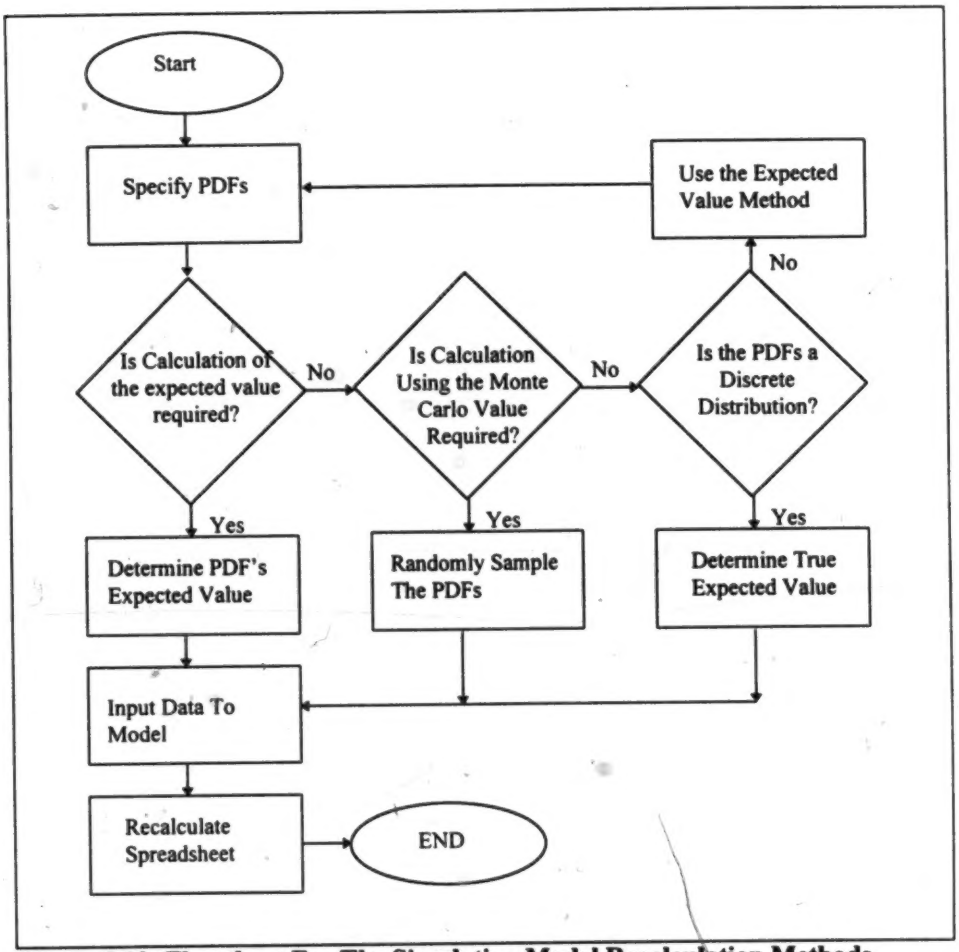


Figure 5.10: Flowchart For The Simulation Model Recalculation Methods.

The first step in the expected value recalculation method is to specify the probability distribution functions. The expected values are calculated for all specified PDFs, and serve as inputs to the stochastic capital budgeting model. Excel uses the expected values to recalculate the function's output which are displayed in the spreadsheet.

The second recalculation option is the Monte Carlo method. The first step in the Monte Carlo method is to specify the PDFs. Random samples are generated from each PDFs, and serve as inputs to the stochastic model. Excel uses these randomly-sampled values to

recalculate the spreadsheet. Thus, the Monte Carlo method results in different values in the stochastic model with each recalculation of the spreadsheet.

The last recalculation option is the true expected value method. This method is the essentially the same as the expected value method, except that it causes all distribution functions, including discrete distributions, to return their expected value during an Excel recalculation. For most applications, the expected value method is recommended, as opposed to the true expected value method. In fact, for a discrete distribution, the expected value method returns a discrete value closest to the true expected value.

@Risk offers two sampling techniques: Latin Hypercube and Monte Carlo as illustrated in Figure 5.9. In this research, the sampling type selected is the Monte Carlo technique which is fully described in Chapter 3.0. Flowcharts detailing both sampling techniques are provided below. Figure 5.11 illustrates the flowchart for the simulation model sampling techniques.

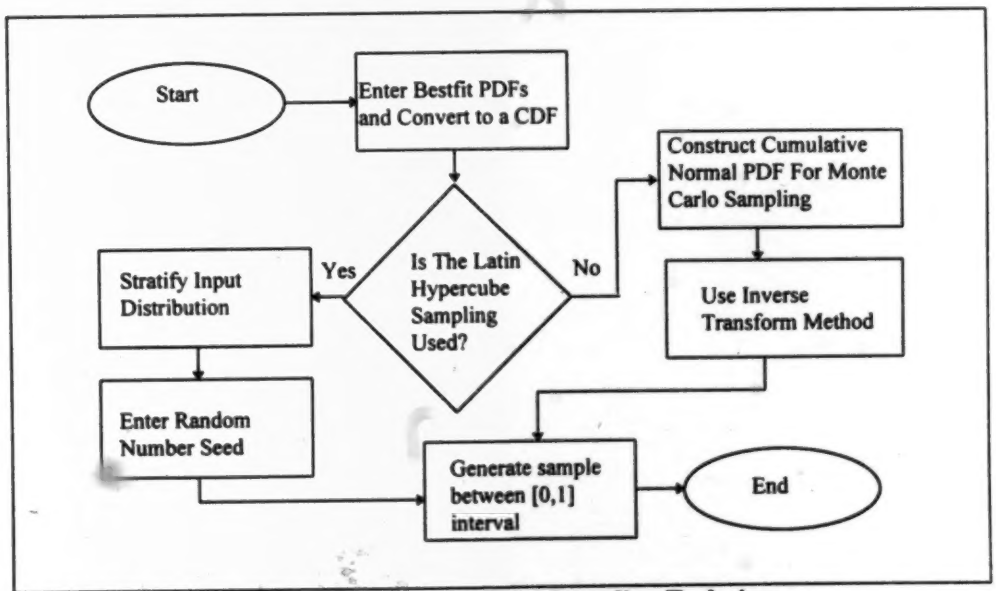


Figure 5.11: Flowchart For Simulation Model Sampling Techniques.

The Latin Hypercube sampling technique is designed to accurately recreate the input distribution by using fewer iterations when sampling the distribution, as compared to the Monte Carlo sampling technique. Once the PDF is entered, it is converted to a cumulative distribution function (CDF). The input distribution is stratified which is a process by which the cumulative curve is divided into equal intervals on the probability scale from [0,1]. Stratification is the primary distinction between the Latin Hypercube and the Monte Carlo sampling techniques. Random samples are drawn from each interval which forces the recreation of the input probability distribution. It is important to note that the number of stratifications of the cumulative distribution is equivalent to the number of iterations selected for a simulation run. For instance, selecting 100 iterations results in the division of the cumulative probability distribution into 100 equal intervals. A sample is drawn from each interval in the sampling process. Once a sample is drawn from a stratification, no other values are sampled from the same stratification

The Monte Carlo sampling technique begins with the construction of a cumulative probability distribution function. Next, a cumulative normal PDF is constructed. An inverse transform methodology is used to transform the cumulative normal PDF into a cumulative uniform distribution. This is a necessary step to permit generating a random sample in the range from [0,1]. From Figure 3.1, it can be seen that a sample is selected along the probability interval from [0,1] by drawing a horizontal line from the cumulative uniform distribution curve across to the cumulative PDF. The result is a corresponding random value along the x-axis.

The random number generator seed permits the user to enter a seed value which is useful in controlling the simulation sampling environment. Entering a non-zero seed value for the random number generator ensures that the exact same sequence of random numbers are going to be repeated during each simulation run. Selecting outputs ensures that only those cells are going to display simulation results. For instance, in this research, only the cell containing the AEC value is selected as an output. The last step before a simulation experiment can be executed requires that one specifies the number of iterations and

simulations. Determining the number of iterations and simulations are established experimentally as described in section 5.2.3. For example, if the desired number of iterations is 1000, then 1000 samples are drawn in a single simulation run. However, two or more simulation runs imply that the spreadsheet is recalculated a total of 1000 times the number of simulations. Figure 5.12 illustrates the flowchart for selecting the number of iterations.

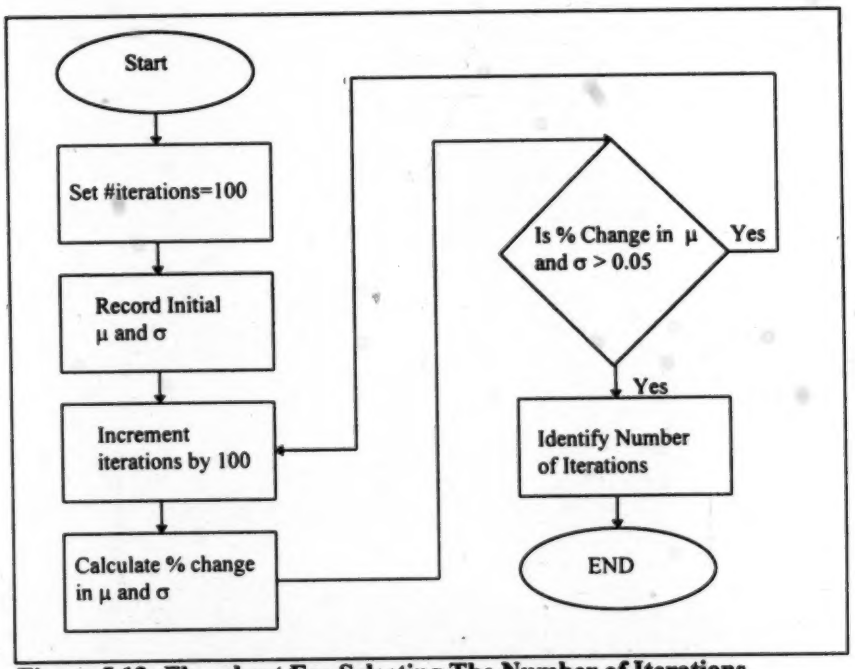


Figure 5.12: Flowchart For Selecting The Number of Iterations.

The process for determining the number iterations is discussed in section 5.2.3. The number of simulation runs used in this study is determined in a similar manner as the one described for determining the number of iterations. Figure 5.13 illustrates the process for determining the number of simulation runs.

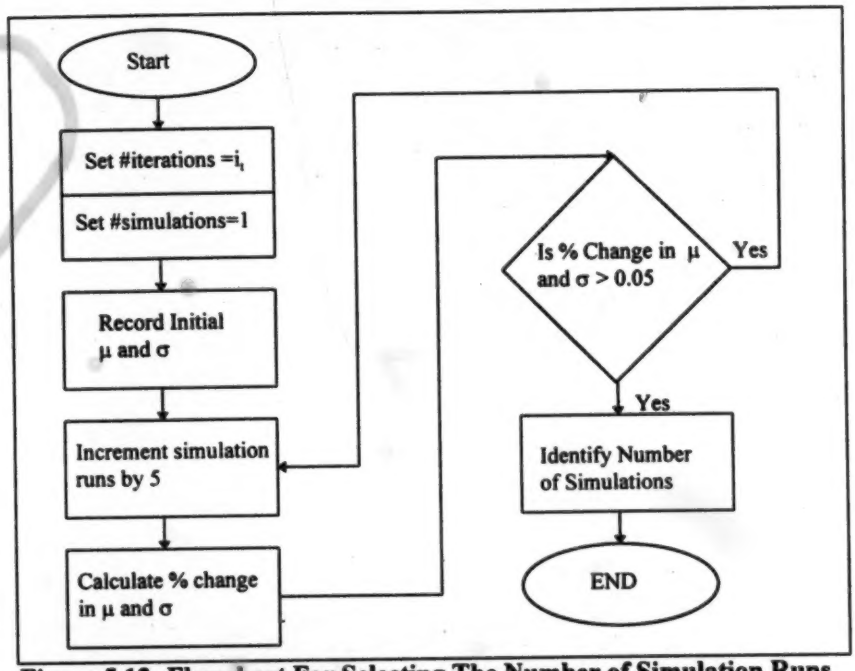


Figure 5.13: Flowchart For Selecting The Number of Simulation Runs.

A critical step in determining the number of simulation runs is to ensure that the number of iterations previously determined is entered in the @Risk simulation setting mode. Otherwise, the algorithm is carried out experimentally in straightforward manner. In fact, it is worth noting that determining the number of iterations is by far the most significant factor in this simulation study.

The simulation model is generates a host of graphical output results. For instance, an output distribution of each stochastic random variable is provided, along with several other graphs which include a frequency and cumulative graphs of the AEC function. A sensitivity analysis is presented in a tornado graph to illustrate which input random variable distributions are significant in determining the output value for the AEC function. It is worth noting that each graphical output can be modified for presentation purposes. For instance, titles, shading, font size and a list of other features are available for performing changes to these graphs. Besides graphical illustrations, @Risk provides

the simulation results in a tabular format which can be extracted and copied onto an Excel worksheet. The simulation results include summary statistics and data reports for both input and output variables. Generated statistics include minimum and maximum values, means, standard deviations, and percentiles. The target value of a random variable, another interesting feature of the simulation results, indicates the probability of achieving (at the most) a desired outcome, or any other value corresponding to a probability level.

5.2 Experimental Design

In this section, the design options matrix is discussed, as well as the required data for validation, and the number of iterations in a simulation run. These design options form the basis for hospital management's selection of a technically and economically feasible design option to solve the MRI problem at Hospital A.

5.2.1 Design Options Matrix

Many design options are available to solve the MRI problem at Hospital A. In this research, a design option is defined as a technically- and economically-feasible option that can be used to solve Hospital A's capital budgeting problem. However, the choice of one option over another largely depends on the cost structure in place, especially in an environment of political and economic uncertainty. For instance, government reduction in hospital funding has triggered a number of problem areas in the delivery of health care services in the province of Alberta [CAC, 1996]. In this research study, a total of seven base options, each with three variant options, have been considered as a sample space for management's decisions. Table 5.1 illustrates the design option matrix developed for this study.

Table 5.1 Design Option Matrix

Base Options	1st Variant Option	2nd Variant Option	3rd Variant Option
UES	UES_1	UES_2	UES_3
CAT	CAT_1	CAT_2	CAT_3
CAR	CAR_1	CAR_2	CAR_3
CPO	CPO_1	CPO_2	CPO_3
LCE	LCE_1	LCE_2	LCE_3
CAH	CAH_1	CAH_2	CAH_3
CMO	CMO_1	CMO_2	CMO_3

Detailed discussions of the base options are provided in Chapter 4.0. The base options represent "full implementation" in the base year 1997 to resolve Hospital A's MRI problem. Subsequently, for example, the first variant option, denoted by the subscript one, considers half implementation in the current base year 1997, while the other half is introduced in the next year (i.e., 1998). The second variant option, denoted by the subscript two, delays implementation by one year relative to current base year; the third variant option is to delay implementation by five years relative to the base year.

5.2.2 Data Gathering and Processing

The source of actual cost information is derived by collecting direct cost data from Hospital A's financial records, and operating data is extracted from the Radiology Department's reports. Indirect costs for the present MRI subsystem are not available from financial records. As a result, they are estimated by determining what comparable costs are incurred from renting equivalent space at a nearby medical building, where the cost of utilities, such as gas and water, are factored into a rental fee. An estimate for power consumption per unit of space is obtained from physical plant personnel at Hospital A. Indirect costs, such as utilities, are always estimated, because hospital subsystems are not individually metered. Other sources of financial information include: Hospital A's annual financial report, and a report prepared by the Radiology Department for Health Region A which address existing MRI problems, and offers potential solutions

[CHA, 1995]. Data was gathered on a monthly basis, because the financial systems accumulate statistical information monthly, and not weekly. Financial reports are generated and distributed monthly to hospital departments [Nestman, 1989; Eastaugh, 1981].

The raw financial data set consists of 30 data points. Each data point represents a monthly accumulation of financial and operational information. In total, the sample data set represents a collection of information for a period of two and one-half years. Monthly expenses incurred by the MRI subsystem are stored in specific locations of Hospital A's general ledger called cost centres. For instance, at the end of a month, all expenditures are added and summarized by cost centres and reported to hospital department managers who will then perform a variance analysis by comparing budgeted (estimated) cost to actual cost. However, a number of cost centres such as minor capital purchases, purchased services and education have information entered in only one or two cells out of a possible 30. Furthermore, there is inconsistent treatment in reporting costs from one month to the next for some cost centres. Nevertheless, monthly financial reports are the best source available for developing unit operating costs in this study. Examples of financial cost data include: staff salaries, interpretation fees, employee benefits, administration salaries, relief staff salaries, drugs, medical/surgical supplies, office supplies, radiology and contrast medium, to name a few.

The reliability of the information collected appears to be adequate, because the data was not altered or massaged in any way. The information was collected and entered without any readjustments to previous accounting periods (i.e., months). At times, collecting information and data for this study presented several difficulties for the author. For instance, it was perceived that information requested for the MRI operation might be used inappropriately. Possibly, the current economic climate contributed to a reluctance to share information for this research study.

Sometimes, the entry and collection of data is inconsistent, and ultimately affects the manner in which the data is processed. No data collection system is completely free of defects, however, the writer believes that the data integrity is adequate for the purpose of this study. In some instances, a subjective value, such as salvage value, is used where it is impractical to collect objective information. Subjective judgment is supported by the author's personal work experience in the healthcare field, and consultation with experts in the field.

The two software programs used in this research to process data include VARSIM and Bestfit. VARSIM is used to define the data gathering scope, for example to help the analyst collect data only on the random sensitive variables, rather than all of the variables in a given sample. These sensitive variables serve as inputs to the Bestfit program. Bestfit attempts to fit a probability distribution function to the stochastic random variables. Once a best fit probability distribution function is found, the stochastic random variables are entered in the capital budgeting simulation model, where they are randomly sampled using the Monte Carlo technique.

5.2.3 Number of Iterations in a Simulation Run

An experimental design is used to validate the required number of iterations for a single simulation run. Many simulation runs can be conducted; however, the most important parameter is to ensure that one carries out a sufficient number of iterations. Otherwise, undertaking many simulation runs, with insufficient iterations, often can result in bi-modal distributions. A new mean and standard deviation is calculated for both the AEC and cost per MRI exam, whenever a value is randomly sampled from the Bestfit distributions. As shown in Figure 5.4, initially intervals of 100 iterations for a single run are carried out, each time recording the mean and standard deviation. This process is continued to about 2000 iterations to prepare Figure 5.19, to plot the percent change in both the mean and standard deviation for AEC, and estimated cost per MRI exam. It can be seen that the percent change in both values begin to stabilize between 900 and 2000 iterations. For the purpose of ensuring sufficient accuracy, 1000 iterations is adequate.

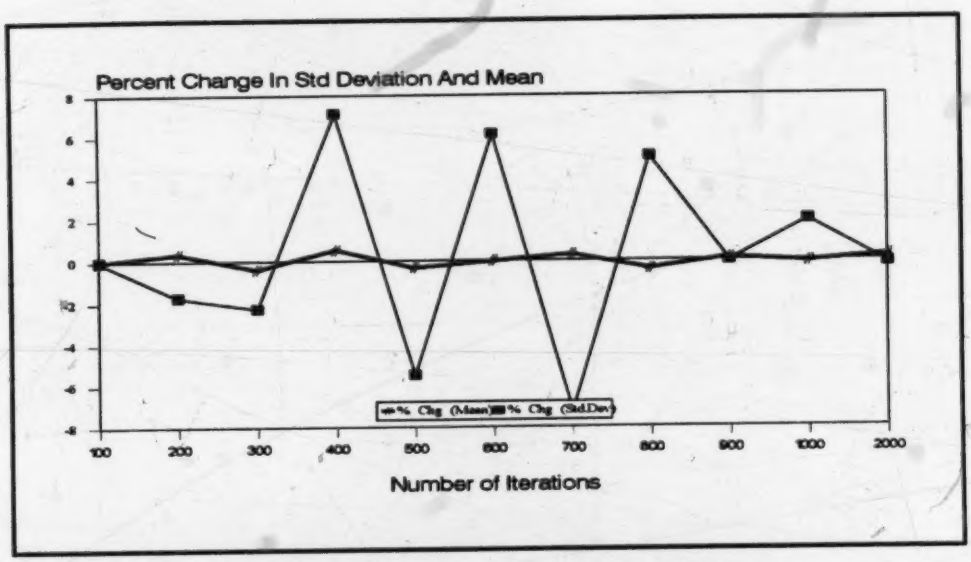


Figure 5.14: Percent Change In Standard Deviation And Mean

5.3 Experimental Setup and Experimentation

The experiment is carried out using a desktop personal computer (PC). The minimum requirements to run the experiment is a 386 DX-33 MHz with Windows 3.0 or higher, with at least eight Megabytes of RAM. However, in this research study, a Pentium 166 MHz PC with 32 Megabytes of RAM is used to carry out the experiment. A Pentium PC offers much quicker processing times, and is able to handle the graphics interface without memory conflicts. The average central processing unit (CPU) time for a simulation run is approximately two to three minutes using a Pentium PC, compared to four to six minutes for the slower PC. The software used in this research study includes two add-in programs, Bestfit v.2.0 and @Risk v.3.5, which are both discussed in sections 5.1, and the Excel v.7.0 spreadsheet. All of these programs are upgraded in order to operate under the current Windows 95 operating system. VARSIM, a DOS-based application is the only other software used in this study.

Off-the-shelf computer hardware and software requirements, plus the computational efficiencies of the software make the use of the concepts in this study practical and helpful in Hospital A's current environment at a relatively low cost.

5.4 Conclusion

The general organization for the experiment begins with first processing the data using VARSIM to determine which random variable significantly explain the total variability in the AEC function. Once these random variables are identified by the VARSIM program, they are further processed using the Bestfit program which fits appropriate distributions to all random stochastic variables. The stochastic capital budget model is coded in the @Risk spreadsheet environment along with fitted probability distribution functions from Bestfit. The simulation settings and parameters are selected before @Risk can be executed. The final output from @Risk is the simulation results for the AEC function, and statistics for the input random variables.

CHAPTER 6.0
DISCUSSION OF RESULTS

In this chapter, the results from the sensitivity and stochastic models are discussed in detail. More specifically, issues and strategies are developed to resolve the problem surrounding Hospital A's Magnetic Resonance Imaging (MRI) operation. The results from the seven base and 21 variant options described in Chapter 4.0 are presented to provide solutions to the problems associated with the MRI system. These problems include: lengthy wait list for MRI exams, increase in demand for MRI services, fiscal constraints on the system, improvement in productivity, maximizing equipment utilization, identifying risk, quantifying opportunity cost gained or lost, and identifying sensitive cost variables relative to the AEC function.

The sensitivity modeling, as described in Chapter 3.0, is carried out by generating system moments for each of the base design options. Generating system moments enables the analyst to determine an estimate of the expected cost from the annual equivalent cost (AEC) function. Furthermore, the analyst can determine, from a variance component analysis, the sensitivity of the AEC function to marginal changes in the random variables by expanding the function about its mean using the Taylor Series expansion to the second order. Calculating the magnitude of partial derivatives of each random variable with respect to the AEC function indicates the relative importance of each random variable to the function.

The VARSIM program described in Chapter 5.0 is used to calculate the system moments and provides a variance component analysis for each of the seven design options. Inputs to the VARSIM program include data collected over a period of two and one-half years from Hospital A's financial and operating records for the MRI system. The financial data is made up of three cost categories: labor, supplies and fixed charges, whereas operating data consists of the number of MRI exams performed annually. The input variable means are coded using FORTRAN 77 language, while estimates for the corresponding standard

deviations are entered via VARSIM's interactive screen display. The output includes an estimated value of an annual expected cost for an MRI exam along with a variance component. Essentially, the moment analysis screens the most sensitive variables among the list of inputs. An advantage to this screening process is that it reduces the cost of data collection. It is not feasible to collect data on an entire set of input data because resources are simply inadequate in the existing economical climate. Furthermore, it is unrealistic to gather information on variables which would not significantly influence the annual expected cost for an MRI exam. The final outcome from the variance component analysis is that only sensitive random variables exhibiting significant variances are selected for further processing. These random variables collectively contribute to the total variation in the AEC for an MRI exam and thus, warrant closer examination than the other input variables.

The selected sensitive random variables are used as inputs in the stochastic models described in Chapter 3.0. The Bestfit package is used to fit each random variable with a probability distribution function (PDF). The selection of an appropriate PDF is based on the goodness-of-fit measure and the comparison of summary statistics as discussed in Chapter 5.0. The stochastic model employs the Monte Carlo sampling technique to sample values from each of the fitted random variables. In this research, the purpose of Monte Carlo simulation is to provide a numerical estimate of the AEC value by evaluating a set of complex mathematical expressions found in the stochastic model. The @Risk program described in Chapter 5.0 is used to invoke the Monte Carlo sampling technique within an Excel environment. Both the base and variant design options undergo a simulation treatment. There are 2,000 iterations generated in a single simulation run. The basis for selecting the number of iterations is described in Section 5.2.3 of this report. Many simulation runs can be conducted; however, the most important parameter is to ensure that a sufficient number of iterations are carried out to ensure variance stability. The simulated range of probable results of the AEC function are displayed graphically in the form of a histogram. In addition, @Risk also provides a set of descriptive statistics to accompany its graphical outputs, so that the user can

observe specific values which are sometimes difficult to visualize from the histogram. VARSIM and Monte Carlo simulation experiments are carried out using a stand-alone personal computer (PC) with a Window95 operating platform. In this research, a Pentium (P-166 MHz) computer with 32 Megabyte of Random Access Memory (RAM) and a 512 internal cache is used to execute the simulation experiments. The average experimental processing time is between five and ten minutes depending upon which design option is being executed.

6.1 Upgrade Existing System (UES) Design Options

The purpose of performing this MRI base option upgrade is to provide Hospital A with the necessary system resources to permit increased operating hours, and to expand its service capacity in order to broaden the range of its services to include: angiographic magnetic resonance MR, cardiac MR and interventional MR. Angiographic MR involves the examination of blood vessels, while cardiac MR involves scans related to the heart.

The base design option represents full implementation at the base year, which in this study is 1997. Under this option, a capital request for three million dollars is required to finance the purchase of hardware and software components necessary to upgrade Hospital A's MRI operation. Approximately 30 percent (0.9M) of the requested sum is allocated to renovation, while the remaining 70 percent (2.1M) is used to purchase both hardware and software components. Upgrading the existing MRI system ensures that operating hours are increased from 50 to 126 hours per week. Newly acquired capital equipment reduces the risk of timely breakdowns, while permitting improved operating efficiency because lower operating costs are expected to be realized from the upgrade.

The targeted operating hours of 126 hours per week is selected on the basis of comparing a similar MRI system in another health region in the same province with a comparable service population. This health region has never experienced problems dealing with timely access to its MRI services, and thus, it does not have to deal with issues surrounding a wait list. At this targeted rate, the MRI wait list at Hospital A would be

more manageable, and not altogether abolished because the current demand is artificial, as pointed out earlier. The expected waiting period is likely to be reduced from six to two months. The impact of increased operating hours translates into an increase from five to seven days per week. Labor requirements are expected to increase by 3.3 "technical" full-time equivalent (FTE) to 5.5 to ensure that adequate staffing is in-place. Equipment utilization would increase from 34.7 to 87.5 percent. Thus, the short-term effects from implementing the UES base design option result in increased capital cost. However, in the long-term, operating and especially maintenance costs are expected to decrease. With this option, Hospital A benefits from higher patient throughput which results in reducing the MRI wait list.

Variation of the base UES design option includes: UES_1, UES_2, and UES_3. The first variant option, UES_1, calls for implementing half of the proposed upgrades in the base year (i.e., 1997) followed by the other half in the second year, say 1998. For instance, the number of proposed exams is equal to the difference between the target and the current volume (i.e., 11,907-4,725) which is equal to 7,182. In other words, UES_1 will handle an additional 3,591 exams in 1997, and the full capacity of 7,182 exams 1998. The advantage of the UES_1 design option is that Hospital A can process additional patients relative to its current workload, and thus, reduce its existing wait list in the short-term. However, a disadvantage is that the expected cost per case is higher than the base case, because high fixed charges are spread over a smaller number of MRI exams. Also, equipment utilization decreases when compared to the base option because operating hours are reduced.

In the second variant design option UES_2, implementation is delayed by one year. In other words, full implementation would not take place until a year after the base year (i.e., 1998). The short-term effects are that the wait list continues to grow for yet another year, while the expected costs per exam remains high. Efficiency of the overall MRI system at Hospital A is likely to remain the same, or decline further due to increased downtime compounded with other scheduled maintenance. The long-term effects from

this option are that equipment utilization increases, productivity rises and overall process efficiency improves. The resulting expected cost per exam in the long-term is higher when compared to the base option, UES and can be directly attributed to the one-year delay.

In the third variant design option UES_3, full implementation of the structural adjustments are delayed by five years relative to the base year. In other words, full implementation is not achieved until the year 2002. The short-term effect is that operating costs continue to increase due to equipment obsolescence, timely repairs, and downtime. It is very likely that the MRI wait list would grow to an unacceptably high rate over the course of five years. Overall, process efficiency is expected to reduce tremendously in the short-term during this same period. Equipment utilization is assumed to remain the same. In fact, all aspects of the existing operation are expected to remain constant with the exception of escalating operating costs. The long-term effect is that the system would be totally unmanageable at the projected cost per exam in five years. In five years, technology is likely to rapidly change, thereby rendering the assumptions made today unrealistic. Once again, the future estimated cost per exam is further compounded by the growth of the opportunity cost.

6.1.1 Functional Moment Analysis Of The UES Option

The functional model described in Chapter 3.0 identifies all of the variables associated with defining the Annual Equivalent Cost (AEC) function. Cost variables for the MRI operation at Hospital A are classified into three cost categories: labor, supplies, and fixed. These cost variables are processed by the VARSIM program which provides the results for the sensitivity model for the UES base option only. Table 6.1 depicts the results of the sensitivity model for the UES design option. It can be seen from the results shown under the %VAR column that seven random variables, highlighted in bold, contribute towards the total variance of the AEC function for the UES design option. The coefficient of variation which is a measure of spread is approximately ten percent, thus

the standard deviations (STD DEV) used for this analysis represent ten percent of their respective means.

Table 6.1 Sensitivity Component Analysis For The UES Design Option

VARIABLE	MEAN	STD DEV	% BIAS	% VAR
Medfee	1,190,700	156,334	0.000	40.48
Medsal	60,011	6,001	0.000	0.06
Relstaff	64,417	19,003	0.000	0.60
Prepay	20,158	0.0000	0.000	0.00
Regest	563,082	187,506	0.000	57.19
Admin	71,561	0.0000	0.000	0.00
Empben	91,565	0.0000	0.000	0.00
Medsurg	5,799	580	0.000	0.00
Conmed	103,959	10,396	0.000	0.23
Drugs	10,474	1,047	0.000	0.01
Radiology	130,501	26,100	0.000	1.45
Conmain	176,819	0.0000	0.000	0.00
Other_supp	71,945	0.0000	0.000	0.00
Fixed	582,014	0.0000	0.000	0.00
Capital	3,000,000	0.0000	0.000	0.00

Total BIAS IN	AEC ($) Per Exam	0.000
Estimated Mean	AEC ($) Per Exam	350
Total STD DEV	AEC ($) Per Exam	21.9

It appears that two of the seven random variables, Medfee and Regest, collectively account for 97.6 percent of the total variance in the AEC function. Medfee expenditure represents fees billed by Radiologists for interpreting MRI exams, while Regest accounts for salaries for all non-medical staff. These two labor related random variables alone consume a significant amount of resources per unit of exam when compared to the

other five random variables. Although the MRI operation is a computerized process, much of the activities surrounding patient throughput requires human intervention. For instance, a nurse is responsible for patient preparation, administering drugs, and to perform injection of dye which acts as a tracer so that the imaging process can scan specific areas of interest. Radiology technicians are responsible for operating the MRI system and to assist in patient preparation. Radiologists are responsible for interpreting the scanned images, and as a result are compensated with a fixed fee per MRI exam. Thus, an increase in both Medfee and Regest are likely to significantly increase the AEC per exam.

Overall, these seven random variables represent variable costs which means that increases in the expected cost fluctuates directly with output changes. However, significant fluctuations are more noticeable with Medfee and Regest than with the remaining five random variables. In short, the upgrade is likely to be impacted collectively by these seven random variables rather than with the remaining cost variables shown in Table 6.1. Although, other cost variables such as Conmain and Fixed remain constant despite fluctuations in output. Conmain is the maintenance contract for servicing the MRI annually, while the variable, Fixed, accounts for charges related to power, water, and heating. As shown in Table 6.1, the expected cost per MRI exam is $350 while the standard deviation is $21.9. These seven random variables are used as input to the stochastic model described in Section 6.1.2. The selection criteria is based on choosing variables which significantly contribute to the total variance in the AEC for MRI exams. The remaining cost variables are insignificant because they have zero variances. By choosing these seven random variables and incorporating them into the stochastic model, meaningful information can be gathered to help explain the uncertainty surrounding the AEC function.

6.1.2 The UES Stochastic Model Input Data

The seven random variables identified in Section 6.1.1 are further processed and fitted with probability distribution functions (PDF) using the Bestfit software package

described in Chapter 5.0 [Palisade, 1996]. The results of the detailed experimental design setup to fit appropriate PDFs to the sensitive random inputs are provided in Table A.11 in Appendix V. The results show that Medfee, Medsal, Relstaff, Conmed, Drugs, Radiology and inflation are all best described by the normal distribution, except for Regest which is described by the lognormal distribution. The normal distribution parameters are simply estimates from the population for the mean, μ, and standard deviation, σ. The distribution parameters for the lognormal distribution include the mean, μ, and standard deviation, σ which are calculated using the formula shown in Appendix V. The salvage value is described by the triangular distribution. The parameters for the triangular distribution for salvage value are based on the following parameters: a = minimum value, b = most likely value, while c = maximum value. These fitted PDFs serve as inputs to the stochastic simulation model for the base and variant options described in Section 5.2.

6.1.3 Stochastic Simulation Results of the UES Design Option

The stochastic model described in Chapter 3.0 is simulated using the Monte Carlo technique. This is achieved using the @Risk package which is run in an Excel environment. The PDFs for selected variables in Table A.11 in Appendix V are used as inputs for the UES simulation model to assist in quantifying the risk and uncertainty associated with the AEC function. The results from the stochastic simulation model for the UES and the variant design options are shown in Table 6.2. From this table, it can be seen that the expected AEC for the base option, UES is $4,171,371 with a standard deviation of $272,826. The MRI operation under the UES base design option would require expenditures at the expected value each year over the next five years. At this level of expenditure, Hospital A can achieve its annual target number of MRI exams equal to 11,907. The distributions for the base and the three variant design options approximate a normal distribution and differ only by their specific statistical parameters (i.e., mean, variance, range etc.) indicated in Table 6.2.

Table 6.2: Summary Statistics of The UES Design Option

Options	Minimum	Maximum	Mean	Std_Dev	Variance
UES	3,384,536	5,545,474	4,171,371	272,826	7.4E+10
UES_1	4,585,256	4,991,442	4,758,939	56,620	3.2E+09
UES_2	5,112,625	7,031,199	5,843,620	250,388	6.3E+10
UES_3	10,891,690	12,279,960	11,599,510	192,642	3.7E+10

Figure 6.1 illustrates the AEC distribution for the UES base and variant options. A shift in the annual equivalent cost for each option is observed. The magnitude in cost for each of the UES design options is directly associated with delaying full implementation. For example, a considerable shift in cost given by UES_3 is associated with delaying full implementation by five years. The first variant option, UES_1, option is plotted separately as shown in Figure 6.2 because its cost structure has a narrow distribution and thus is best illustrated alone.

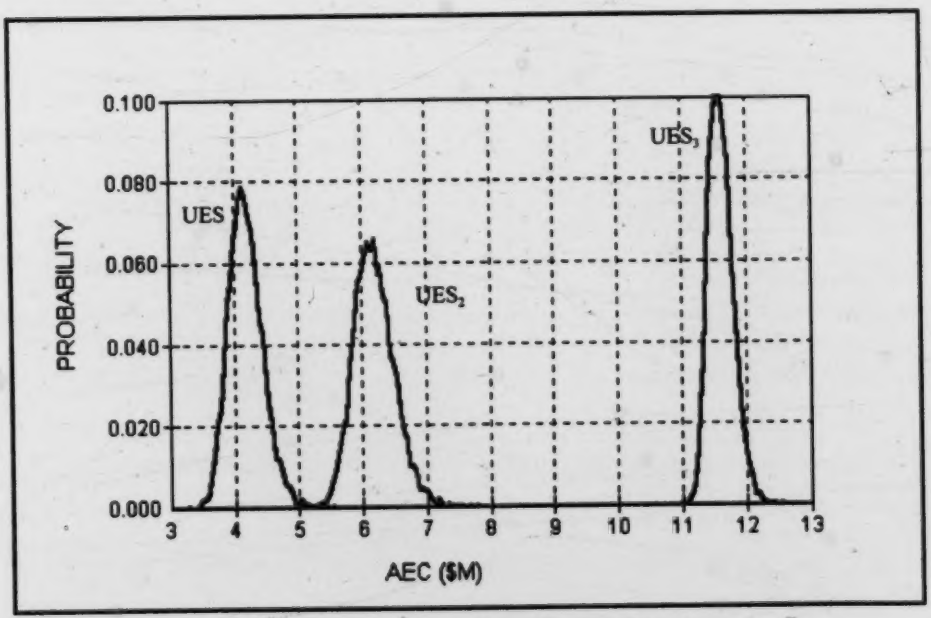


Figure 6.1: AEC Distribution For The UES Base and Variant Options

From Figure 6.2, the UES_1 option appears to approximate a normal distribution and is slightly right skewed which is the case when the mean is greater than the median value.

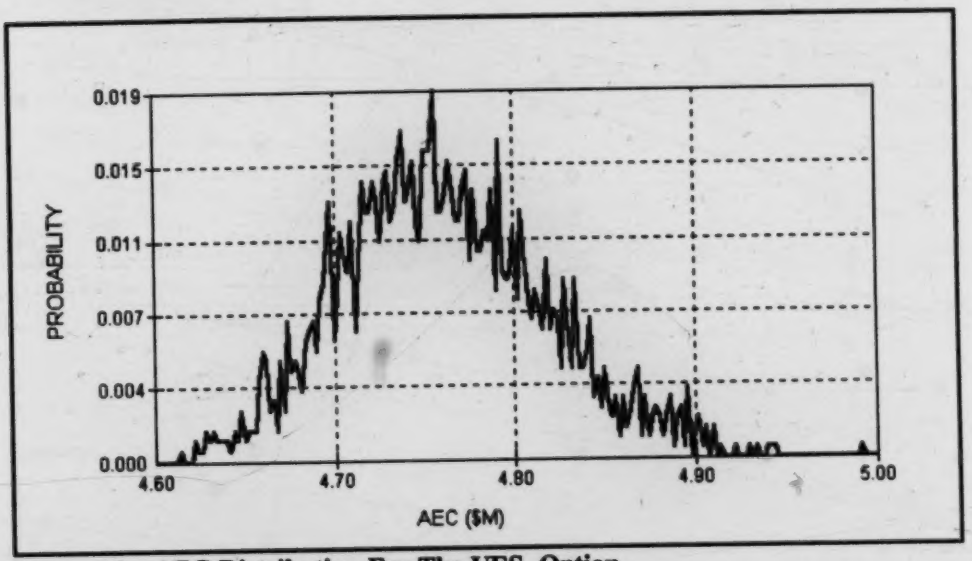


Figure 6.2: AEC Distribution For The UES_1 Option

The AEC range is from \$4.6M to \$5.0M. By observation, there appears to be little variability in the values shown in the AEC distribution. The results in Table 6.2 also show a steady increase in the expected AEC from the base option through to the three variant options. The unit cost of the MRI system clearly shows this increasing trend in cost for each design option. Figure 6.3 illustrates the expected cost per exam for the base option and the three variant design options. From this figure, the base design option is the most cost effective when compared to the three variant options. For instance, by implementing the base option today (i.e., during the base year 1997), Hospital A can achieve the targeted annual MRI exams at a cost of \$350 per exam. However, delaying implementation of the base option can result in significant cost increases. For instance, increases in cost can be attributed to lost opportunity cost, cost of financing MRIs today, escalating charges for labor, supplies, and utilities.

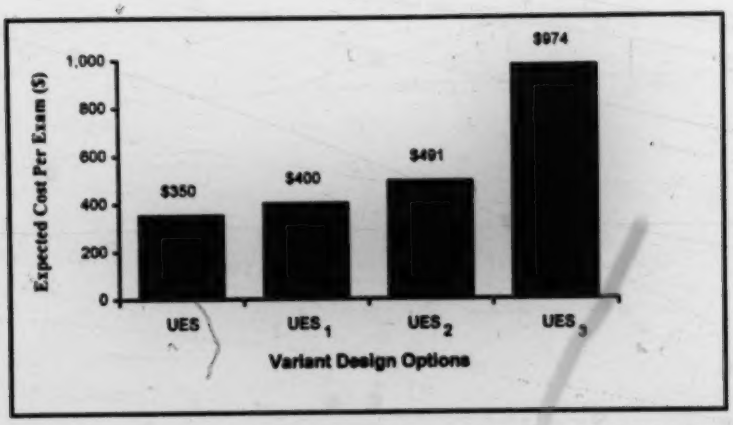


Figure 6.3: Expected Cost Per Exam For The UES Design Options

Figure 6.4 also shows the cost increases for the variant options relative to the base option. The respective percentage cost increases for UES to UES_1, UES to UES_2, and UES to UES_3 are about 14.1, 40.1, and 178.1 respectively.

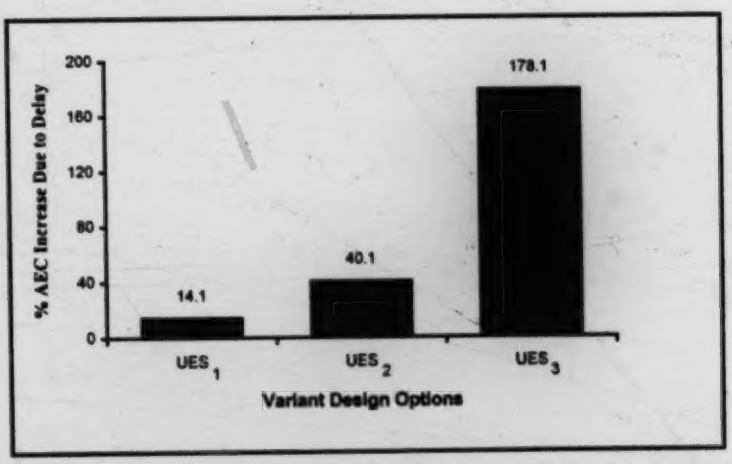


Figure 6.4: Percent Increase Due To Delay Of Base Option

Figure 6.5 illustrates also the opportunity cost gained or lost by selecting a particular design option. The opportunity cost represents the difference between the present cost of an MRI exam and the proposed cost for each design variant option. The magnitude of the opportunity cost depends on lost production, high operating cost, inflation adjusted

discount rate, inflation rate, and the wait list. All of these factors combined significantly affect the magnitude of the opportunity cost. For example, the high operating cost of the existing MRI system is compounded by delaying full implementation, and thus is captured in the opportunity cost.

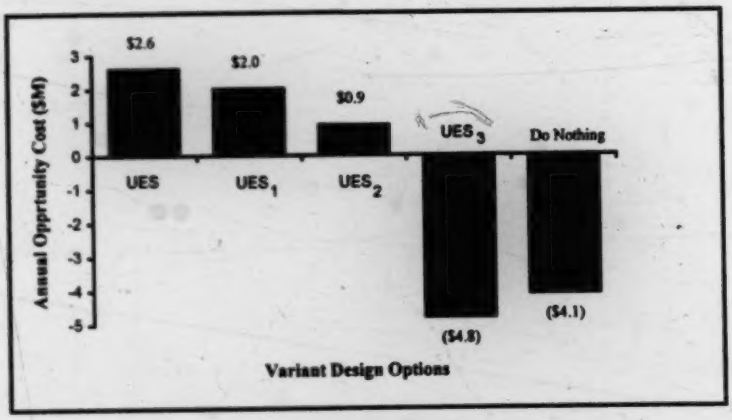


Figure 6.5: Opportunity Cost Gained (Lost) Annually

This figure shows that the opportunity cost saving is greatest with the base option, and this saving decreases with increasing delay periods. Full implementation of the UES base design option today allows Hospital A to save a total of $2.6M annually; UES_1 saves $2.0M; and UES_2 saves $0.9M. These savings can be reinvested to improve services in other departments found in Hospital A. However, with the third variant option UES_3, and the option for doing nothing, there are respective losses of $4.8M and $4.1M. The Do Nothing option offers no benefit to Hospital A. Hospital A must spend $4.1M to alleviate the backlog of patients and yet maintain control of the MRI wait list. Thus, decision-makers must carefully examine the cost implications associated with each design option, because the choice of design option can significantly affect the operation of other hospital departments. These results demonstrate the need for undertaking swift action to save the MRI system.

Another important element for decision-makers to consider is the risk of failure. The risk of failure provides a probabilistic measure for not achieving the system's performance objective. Table 6.3 lists the expected cost per MRI exam, and the probability of success for attaining these values for each UES design option. From this table, the probability of achieving $350 per exam is 53 percent for the base UES option. The probability of failure associated with this cost structure is simply (1-p).

Table 6.3: UES Expected Cost Per Exam and Associated Probabilities

Options	Expected Cost Per Exam	p (probability of success)
UES	$350	53 %
UES_1	$400	53 %
UES_2	$491	52 %
UES_3	$974	53 %

Risk profiles are generated for providing a range of probable outcomes so that decision-makers can carefully assess potential risk of failure associated with each estimated cost per exam. Figure 6.6 illustrates the probability profile for the UES base and variant options. The expected cost per exam can be estimated for a specific probability. Decision-makers can use this chart to predict the probability of failure and its associated cost structure. From this figure, the lower (LL) and upper (UL) parameters of the UES base option define the limits of the possible cost estimates associated with the UES base option. LL and UL indicate the expected cost estimates with 100 and zero percent probability of failure. A unit cost of $284 per exam associated with the UES option is unattainable economically. At a unit cost of $460 per exam, the option is over-designed with no risk at all.

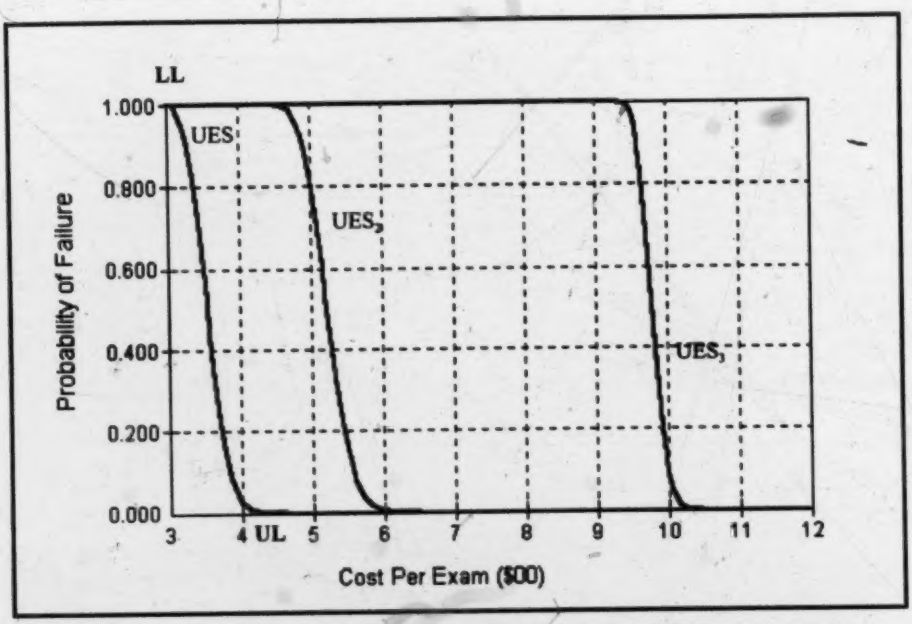


Figure 6.6: Probability of Failure For The UES Base and Variant Options

In other words, by seeking such an unrealistic unit cost estimate of $284 per exam, Hospital A faces an impossible task in meeting the organization's objectives (i.e., attaining the annual number of MRI exams). At a 100 percent risk of failure, Hospital A cannot attain its targeted output of 11,907 exams per annum, or maintain a sufficient level of operating efficiency, because financial resources are simply inadequate. With no inherent risk, Hospital A is committing to over-spending to achieve its targeted output. Unfortunately, the operating efficiencies of other subsystems are certain to suffer from such an excessive MRI cost. From this diagram, the LL and UL shifts to $429 per exam with 100 percent failure probability and $591 per exam with zero percent failure probability for the UES_2 option. Delaying full implementation by five years significantly affects the unit cost of an MRI exam. The expected cost per exam for UES_3 is almost three times the expected cost for the base option and is significantly higher than UES_1 and UES_2. Once again, the LL and UL shifts to $915 per exam with 100 percent failure probability and $1,031 per exam with zero percent failure probability. The risk associated with the five year delay results in other non-quantifiable costs such as the cost

of patient suffering while awaiting an MRI exam. It is difficult to attach a cost associated with mental and physical anguish. Consider an individual suffering from frequent migraines who is told that he/she must wait six months for an MRI exam. The waiting period is very likely to affect the individual's personal and professional productive capacity. Furthermore, these patients are going to have a negative impact on the health system through frequent visits to physicians which often results in increased medication. Medication cost, to a large extent, is subsidized by the government.

The UES_1 MRI option has been extracted to show a more defined estimated cost range and its associated probabilities as illustrated in Figure 6.7.

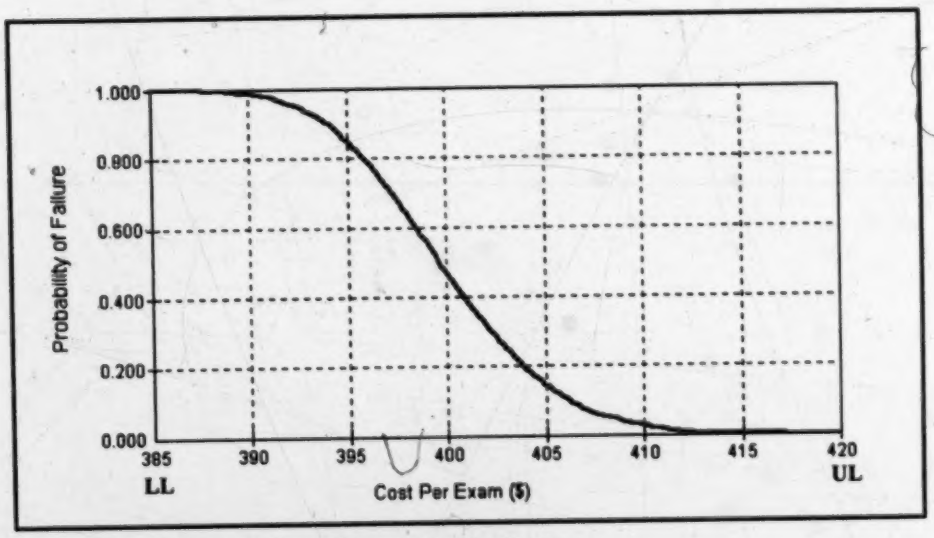


Figure 6.7: Risk of Failure For The UES_1 Option

The critical lower and upper limits for UES_1 are $385 per exam with 100 percent failure probability and $419 per exam with zero percent failure probability. Hospital managers can opt for UES_1 option, however, they are faced with spending at a higher level relative to the base option to achieve the annual target MRI exams, despite having similar probability values as indicated in Table 6.3.

6.2 Computed Axial tomography (CAT) Design Option

The objective of this design option is to purchase an additional CAT scan to relieve the workload of the MRI department at Hospital A. The resulting outcome is to reduce the growing number of patients currently awaiting an MRI exam. A profile of the existing workload suggests that over 80 percent of patients receive an MRI exam for neurological related disorders as shown in Table A.12 in Appendix V. Thus, the CAT design option would be an acceptable diagnostic method for detecting neurological related disorders.

The base option which represents full implementation during the base year requires that Hospital A purchase a second CAT scan. The capital requirements for this purchase are estimated to be $1.6 million dollars. The acquisition of a second CAT scan results in increased operating hours per week from 10 to 16, and permits Hospital A to perform an additional 7,182 exams necessary to reduce the MRI wait list. Labor resources must increase by an additional 1.5 FTE to accommodate increased operating hours. The target number of exams for the base CAT option is set at 7,182 to enable Hospital A to attain its annual target number of MRI exams. The target for the CAT option represents the difference between Hospital A's annual target and its existing throughput.

The short-term effect of the base CAT option is that Hospital A does not commit resources towards upgrading the existing MRI system. The wait list is expected to decrease, however, operating hours for Hospital A's MRI system are likely to increase from 50 to 88 hours per week to absorb CAT scans exams which reveal insufficient diagnostic information. Consequently, operating expenses are certain to increase. For example, the MRI department needs to increase its labor by at least 2.0 FTEs to ensure adequate staffing is available. The MRI equipment utilization is expected to increase from 35 to 61 percent. The basis for this additional cost to the MRI system is that the CAT option cannot always accurately reveal vital information surrounding soft tissue areas of the body. As such, it is assumed that approximately half of the CAT scans performed must be re-examined using the MRI scanner. This particular re-examination feature is applicable only to the CAT design option. Unfortunately, long-term

implications of the CAT option are such that operating and especially maintenance costs, are likely to increase appreciably for the MRI system, unless necessary repairs and upgrades are carried out. Without appropriate upgrades, the existing MRI system is bound to encounter frequent downtime which is certain to impact the wait list. In other words, the wait list is likely to experience significant growth as a result of patient cancellations and re-scheduling due to frequent downtime.

Variation of the base CAT design option includes: CAT_1, CAT_2, and CAT_3. The first variant option CAT_1 calls for implementing half of the proposed number of exams in the base year (i.e., 1997) followed by the other half in the second year, say 1998. For instance, the number of proposed exams is equal to the difference between the target and the current volume (i.e., 11,907-4,725) which is equal to 7,182. In other words, half of 7,182 exams are implemented in 1997, while the other half is introduced in 1998. The advantage to the CAT_1 design option is that Hospital A can process additional patients relative to its current workload, and thus, reduce its existing wait list in the short-term. However, a disadvantage is that the expected cost per case for the CAT_1 option is higher than the CAT base case, because high fixed charges are spread over a smaller number of exams. Furthermore, the opportunity cost associated with delaying implementation of the base case must be thoroughly examined.

The second variant design option CAT_2 is to delay full implementation by one year. In other words, full implementation would not take place until a year after the base year (i.e., 1998). The short-term effect is that the wait list continues to grow for yet another year, while the expected costs per exam remains high. Efficiency of the overall MRI system at Hospital A is likely to remain the same, if not decline further due to increased downtime compounded with other scheduled maintenance. The long-term effects from the CAT_2 option is that patient throughput increases, combined with a decrease in the wait list. Unfortunately, the opportunity cost due to the one-year delay deeply affects the expected cost per case for this design option which is discussed later in this section. The

resulting expected cost per exam in the long-term is higher when compared to the base option, CAT and can be directly attributed to the one-year delay.

The third variant design option CAT_3 is to further delay full implementation by five years relative to the base year. In other words, full implementation is not achieved until the year 2002. The short-term effect is that operating costs for the existing MRI system continues to rise due to equipment obsolescence, timely repairs, and downtime. The MRI wait list would grow to an unacceptably high rate over the course of five years. Overall, process efficiency is expected to decrease significantly in the short-term during this same period. Equipment utilization is assumed to remain the same. In fact, all aspects of the existing operation are expected to remain constant with the exception of escalating operating costs. It is reasonable to assume that the system would be uneconomical at the projected cost per exam in five years. In five years, an important factor such as technology is likely to rapidly change, thereby rendering the assumptions made today unrealistic. Once again, the future estimated cost per exam is further compounded by the growth of the opportunity cost.

6.2.1 Functional Moment Analysis Of The CAT Option

The cost variables which define the AEC and the results from the VARSIM sensitivity analysis for the CAT design option are shown in Table 6.4. The cost variables are classified into three categories: labor, supplies, and fixed charges. These cost components are collected from Hospital A's Annual Return of Healthcare Facilities – a financial instrument which requires hospitals to report annual expenditures and workload statistics. The number of CAT scans are also extracted from this return. Both the financial and workload statistics for the CAT design option are entered into the VARSIM program. The results indicate that four sensitive random variables are present. These random variables identified in bold type include: Medsal, Medfee, Regest, and Medfee. In total, these four labor related random variables contribute to the total variation in the AEC function. However, Medfee alone explains 79.6 percent of the variation in the AEC function. Significant influences in the AEC function for a CAT exam are exerted by

Medfee which accounts for all expenditures related to interpretation of CAT scans. In other words, it represents a fee-for-service billed by Radiologists. This is a negotiated fee between physicians and the Alberta government. Unfortunately, Hospital A would have a difficult time negotiating a lower rate due to varying levels of bureaucracy. The next significant random variable is Regest, which represents non-medical staff salaries.

Table 6.4 Sensitivity Component Analysis For The CAT Design Option

Variable	Mean	STD DEV	% BIAS	% VAR
Medsal	366,991	36,699	0.000	3.88
Regest	698,202	69,820	0.000	14.04
Medfee	1,661,920	166,192	0.000	79.55
Supplies	261,997	0.0000	0.000	2.54
Fixed	159,935	0.0000	0.000	0.00
Capital	1,600,000	0.0000	0.000	0.00

Total BIAS IN	AEC ($) Per Exam	0.000
Estimated Mean	AEC ($) Per Exam	510
Total STD DEV	AEC ($) Per Exam	15.96

It is conceivable that Hospital A can negotiate a reduction in salaries; however, this approach involves ratifying a collective bargaining agreement between Hospital A and the union representing its staff members. Unfortunately, it appears that the only method for cost containment is to either reduce the level services or convince radiologists to accept a reduced fee-for-service. Thus, it is clear that hospital managers should closely monitor Medfee followed by Regest. Increases to both Medfee and Regest are certain to cause significant increases in the AEC for a CAT scan exam. These four random variables are fitted with PDFs in Section 6.2.2 and serve as inputs to the stochastic model for the CAT design option described in Section 6.2.3.

6.2.2 The CAT Stochastic Model Input Data

The four random variables identified by VARSIM's sensitivity component analysis in Section 6.2.1 are further processed and described by a normal PDF. The statistical parameters for the normal distribution include population estimates for the mean and the standard deviation. A coefficient of variation of ten percent is used to provide an estimated value for the standard deviation. Salvage value is another random variable which is described by a triangular distribution. The statistical parameters describing the random variables are summarized in Table A.12 in Appendix V. Graphical results of the fitted input random variables are also included in Appendix V.

6.2.3 Stochastic Simulation Results of the CAT Design Option

The stochastic model for the CAT design options is programmed into an Excel spreadsheet to evaluate the base and variant options for the CAT design option. The fitted PDFs found in Table C in Appendix V are used as inputs in simulating the CAT model which is used to assess and quantify risk associated with the AEC function. The results from the stochastic simulation model of the CAT design option and its variant options are shown in Table 6.4.

Table 6.5: Summary Statistics of The CAT Design Option

Options	Minimum	Maximum	Mean	Std_Dev	Variance
CAT	5,791,909	6,294,278	6,078,704	70,255	4.9E+09
CAT_1	6,545,156	6,604,003	6,574,056	8,932	8.0E+07
CAT_2	7,666,571	8,083,559	7,867,770	70,201	4.9E+09
CAT_3	12,526,120	13,013,750	12,726,080	66,056	4.4E+09

The results in Table 6.4 indicate that the expected AEC for the CAT design option increases from the base through to each of its variant options. The choice of one design option over another is governed by a specific annual equivalent cost structure. For example, the AEC for the base design option, CAT, is $6,078,704 with a standard deviation equal to $70,255. Hospital A can achieve its annual target number of MRI

exams, only if it spends at this level each year over the next five years. Otherwise, it cannot expect to meet its annual target of MRI exams. The distribution of the AEC for the base CAT option and its variant options are presented in Figure 6.8. The shift in costs are apparent with delaying full implementation as indicate by CAT_2 and CAT_3. Costs associated with CAT_1 are illustrated separately in Figure 6.9 because its cost structure is too narrow.

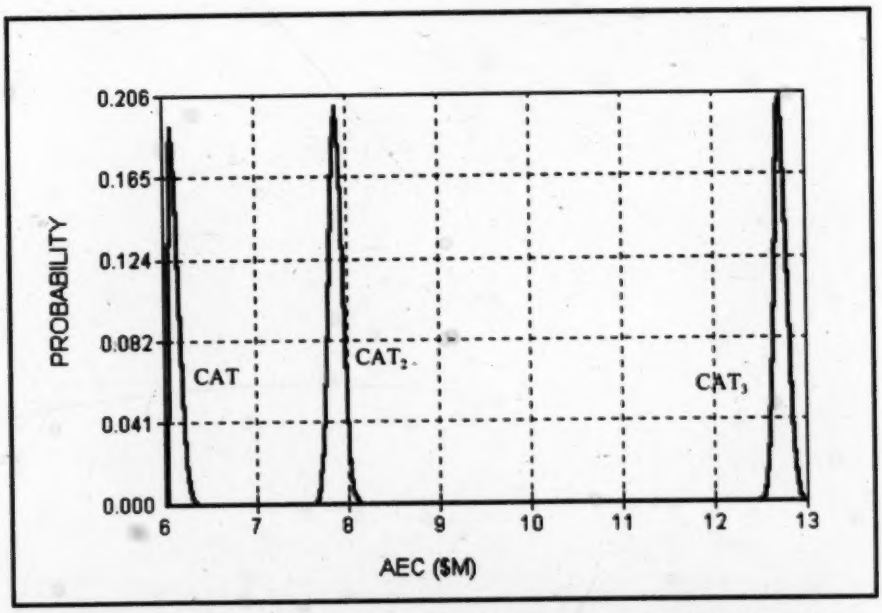


Figure 6.8: AEC Distribution For The CAT Base and Variant Options

A closer examination of the first variant option, CAT_1, reveals that the distribution is approximately normal. The AEC range is from \$6.5M to \$6.6M with a standard deviation of \$8,932. It is clear that the AEC range for the CAT_1 option is narrow. In this situation, it is best to isolate it from the rest of the CAT AEC distributions as shown in Figure 6.8.

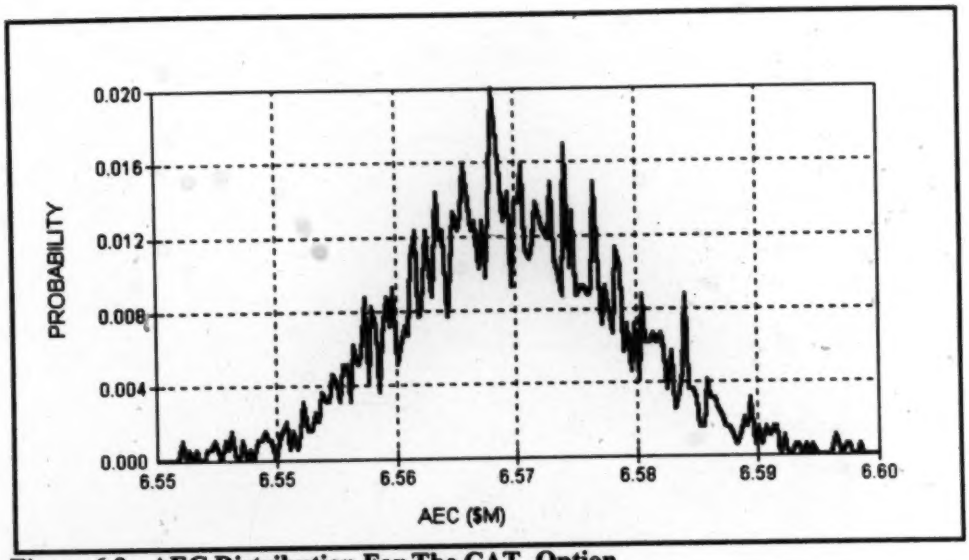


Figure 6.9: AEC Distribution For The CAT_1 Option

The AEC when expressed per MRI exam, clearly shows the increasing trend in AEC for the base and each of its variant design option indicated in Table 6.4. Figure 6.10 illustrates the expected cost per exam for the base option and the three variant design options.

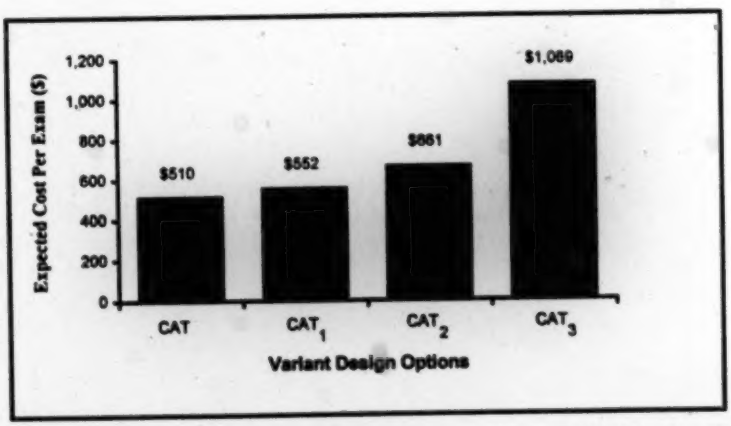


Figure 6.10: Expected Cost Per Exam For The CAT Design Options

From this figure, delaying full implementation (i.e. CAT base option) is associated with increasing costs as demonstrated in the each of the variant design options. Implementing the base option is more cost effective when compared to its three variant options. A graphical representation of the percent increase in cost relative to the base option (full implementation today) is illustrated in Figure 6.11. This figure also demonstrates the magnitude of cost implications associated with delay of the base CAT option. The respective percentage cost increases for CAT to CAT_1, CAT to CAT_2, and CAT to CAT_3 are about 8.2, 29.6, and 109.6 respectively. Increases in cost can be attributed to lost opportunity cost, cost of financing, escalating labor rates, and increases in supplies and fixed charges.

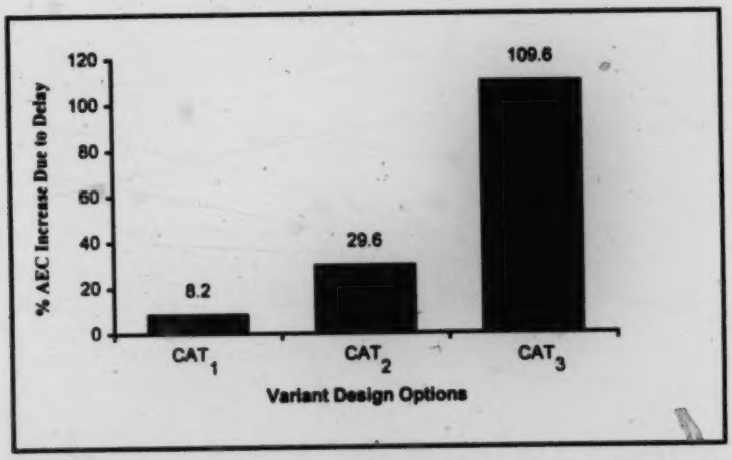


Figure 6.11: Percent Increase Due To Delay Of Base Option

The opportunity cost associated by selecting one CAT design option over another presents useful information to decision-makers when evaluating alternative investment strategies to resolve Hospital A's MRI problems. Figure 6.12 illustrates the opportunity cost gained or lost by selecting a particular design option. The magnitude of the opportunity cost depends on the factors listed in Section 6.1.3. Some of these factors include: lost production, high operating cost and general price level increases. For example, implementing the CAT base option allows Hospital A to save a total of $0.7M

annually; and CAT_1 saves \$0.2M. However, with the variant options CAT_2, CAT_3, and the do nothing option, there are respective losses of \$1.1M, \$6.0M and \$4.1M. The annual savings experienced by choosing CAT or CAT_1 design option can be reinvested in other areas of the hospital to assist in improving services. Unfortunately, if any of the following variant options, CAT_2, CAT_3, or the do nothing is selected, then annual losses arising from these options are certain to be absorbed by Hospital A's operating budget. Otherwise, Hospital A cannot ensure that its annual MRI target exams are achieved. Furthermore, it is reasonable to assume that funding such losses affects the operation of other departments who are likely to experience a shortfall in their operating budget.

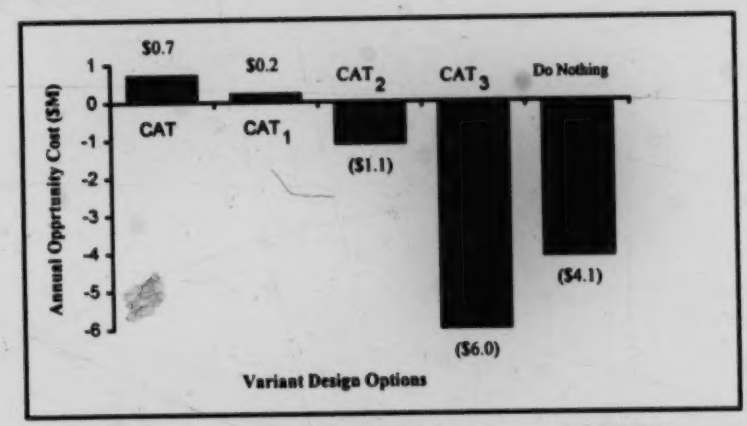


Figure 6.12: Opportunity Cost Gained (Lost) Annually

The probability of achieving annual target MRI exams associated with each design option is given in Table 6.6. It can be seen that a 51 percent chance exists in achieving the expected cost of \$510 per MRI exam which is necessary to attain the annual target number of MRI exams (i.e., 11,907). If decision-makers select CAT_1 option, then they must be willing to spend at a higher level (i.e., \$552) to achieve the same probability of achieving the annual target MRI exam. From Table 6.5, similar probabilities of success exist for achieving the annual target MRI exams for CAT_2 and CAT_3 options when compared to CAT and CAT_1 options. However, the expected cost per exam to achieve the similar probabilities of success for these last two variant options increase significantly.

Thus, decision-makers must carefully evaluate both components, the probability of success and the expected cost per exam necessary to achieve the annual target number of MRI exams.

Table 6.6: CAT Expected Cost Per Exam and Associated Probabilities

UES Options	Expected Cost Per Exam	p (probability of success)
CAT	$510	51 %
CAT_1	$552	51 %
CAT_2	$661	52 %
CAT_3	$1,069	51 %

A risk profile illustrates the risk of not achieving the estimated cost per exam. Figure 6.13 demonstrates the risk of failure associated with the CAT base and its variant options.

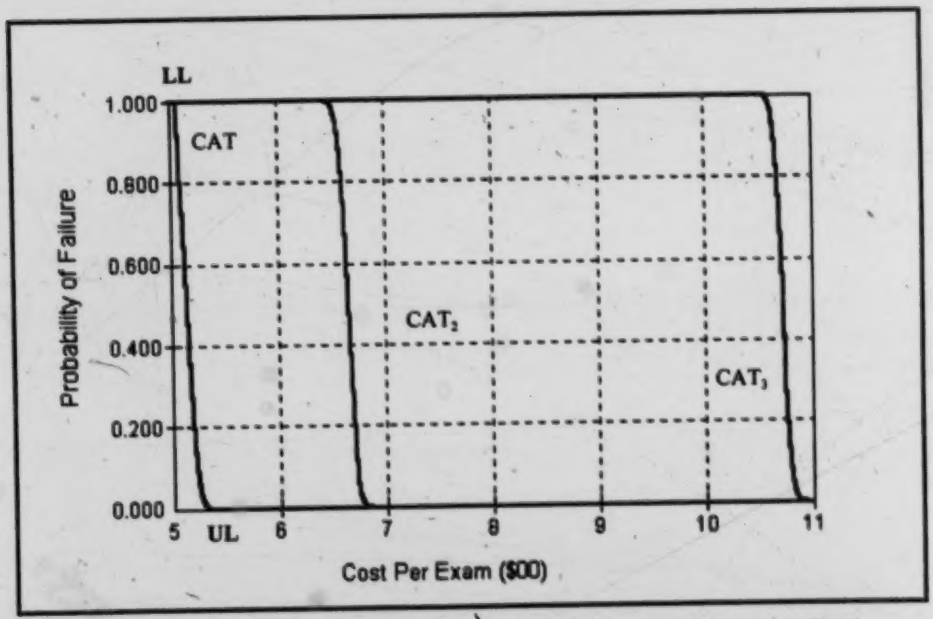


Figure 6.13: Probability of Failure For The CAT Base and Variant Options

The risk of failure and its associated costs can be estimated from Figure 6.13. Cost per exams are highest among CAT2 and CAT3, regardless of the probability of failure. From

this diagram, the LL and UL for the base CAT option is $486 per exam with 100 percent failure probability and $529 per exam with zero percent failure probability. The critical limits shift significantly with CAT_2 and especially, CAT_3. Figure 6.14 illustrates the risk profile for the CAT_1 option. It can be seen that a 100 percent chance of failure occurs at $550 per exam which is denoted by the lower limit, LL. In other words, by seeking such an unrealistic objective, Hospital A faces an impossible task in meeting the organization's objectives (i.e., attaining the annual number of MRI exams). At a 100 percent risk of failure, Hospital A cannot attain its targeted output of 11,907 exams per annum, or maintain a sufficient level of operating efficiency, because financial resources are simply inadequate.

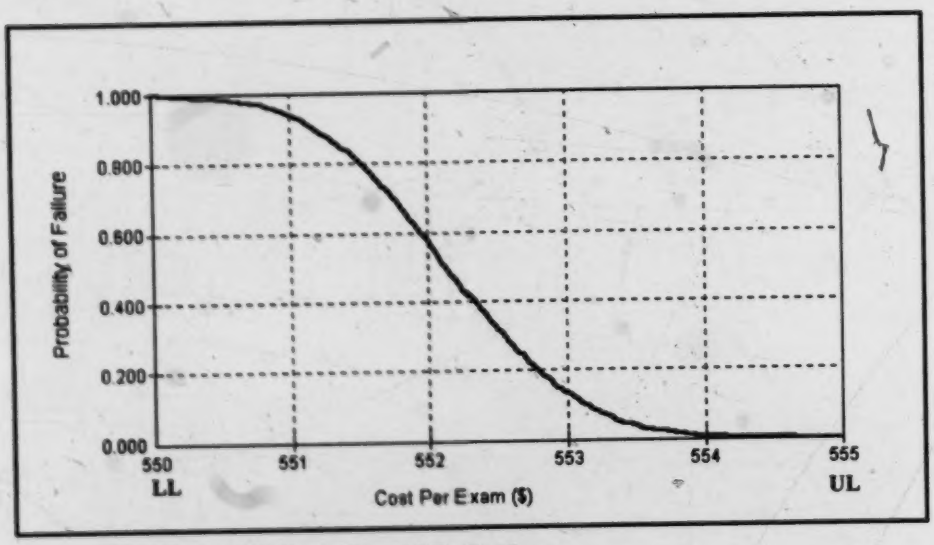


Figure 6.14: Risk of Failure For CAT_1 Option

The upper limit given by UL, occurs at $555 per exam. At UL, Hospital A takes no risk of not being able to attain its targeted MRI output level. However, by not taking a risk, Hospital A is committing to over-spending to achieve its targeted output. Unfortunately, the operating efficiencies of other subsystems are certain to suffer from such an excessive MRI cost. Similar risk profiles can be constructed for the three CAT variant options to convey risk management information to decision-makers.

6.3 Contract Another Region (CAR) Design Option

The purpose of contracting another region is to enable Hospital A to achieve its annual target MRI exams (i.e., 11,907) necessary to satisfy the demand for MRI services in Health Region A. Hospital A would contract a total of 7,182 MRI exams to its neighbor, Health Region B which has sufficient capacity to perform these exams, in addition to their own. In the short-term, Hospital A can continue to operate its existing MRI system without performing any of the necessary upgrades. Resources not used for upgrading purposes would be allocated to reimburse Health Region B for the provision of its MRI services. The result is that the existing wait list would decrease, and provide patients with greater access to MRI services. However, in the long-term, operating costs for Hospital A's MRI system is expected to rise due to factors such as equipment deterioration and obsolete parts. Also, these factors are likely to contribute toward a decline in equipment utilization. It is inevitable that overall productivity and process efficiency at Hospital A are certain to suffer in the long-term.

6.3.1 Functional Moment Analysis Of The CAR Option

The cost variables which define the AEC and the sensitivity component analysis for the CAR design option are shown in Table 6.7. All of the costs shown are variable in nature which means that they are dependent on throughput. In this case, total expenditure is dependent on the number of MRI exams carried out. The sensitive random variables for the CAR option are highlighted in bold.

The results shown in Table 6.7 indicate that three random variables: charter, accommodation, and meal collectively explain 100 percent of the variation in the AEC function. The non-random variable given by price is the rate for an MRI exam. This rate covers only a portion of the overall cost of an MRI exam under the CAR option. The remaining costs are determined by the three sensitive random variables which can significantly influence the AEC for MRI exams.

Table 6.7 Sensitivity Component Analysis For The CAR Design Option

Variable	Mean	STD DEV	%BIAS	%VAR
Price	650	0	0.000	0.00
Charter	323,190	32,319	0.000	37.33
Accommodation	359,100	35,910	0.000	46.08
Meal	215,460	21,546	0.000	16.59

Total BIAS IN	AEC ($) Per Exam	0.000
Estimated Mean	AEC ($) Per Exam	708
Total STD DEV	AEC ($) Per Exam	6.73

For example, charter cost explains 37.3 percent of the total variance in the AEC, while accommodation explains an additional 46.1 percent of the total variation. Charter represents expenditure related to transportation costs, whereas accommodation cost accounts for an overnight stay. Increases in either of these two random variables can greatly affect the overall cost for an MRI exam. For instance, increases in fuel price are likely to cause an upward shift in transportation rates, whereas seasonal factors can result in either higher or lower hotel rates, depending on the time of year. The third random variable, meal, accounts for food charges. It explains only 16.6 percent of the total variation in the AEC and is not likely to significantly impact the AEC as compared to the other two random variables. These three random variables are used as inputs to the stochastic model described in Section 6.3.2. The selection criteria is based on the approach specified in Section 6.1.1.

6.3.2 The CAR Stochastic Model Input Data

The three random variables identified in Section 6.3.1 are further processed and described by a normal probability distribution function (PDF). The results of the detailed experimental design to fit PDFs to the three sensitive random inputs are provided in Table A.13 in Appendix V. The results in Table A.13 show that charter, accommodation,

and meal are all fitted with a normal PDF. The normal PDF includes statistical parameters for the mean and standard deviation.

6.3.3 Stochastic Simulation Results of the CAR Design Option

The fitted PDFs described in Section 6.3.2 are used as inputs to the stochastic model. The simulation is carried out using the @Risk package which invokes the Monte Carlo sampling technique. The results from the stochastic simulation model for the CAR and the variant design options are shown in Table 6.8.

Table 6.8: Summary Statistics of The CAR Design Option

Options	Minimum	Maximum	Mean	Std_Dev	Variance
CAR	8,287,101	8,562,713	8,432,230	44,609	2.0E+09
CAR_1	8,746,419	8,787,109	8,767,855	5,828	3.4E+07
CAR_2	9,825,555	10,118,540	9,976,881	43,952	1.9E+09
CAR_3	14,382,460	14,620,660	14,501,990	32,851	1.1E+09

The results in Table 6.8 indicate that the expected AEC increases from the base option, CAR through to each of the variant options given by CAR_1, CAR_2 and CAR_3. The expected AEC for each design option is the level of expenditure which Hospital A must maintain each year to ensure that it attains its annual target number of MRI exams. The AEC distribution for the CAR base option and its variant options are illustrated in Figure 6.15. There is a significant shift in cost between options CAR to CAR_2 and more noticeably from CAR_1 to CAR_3.

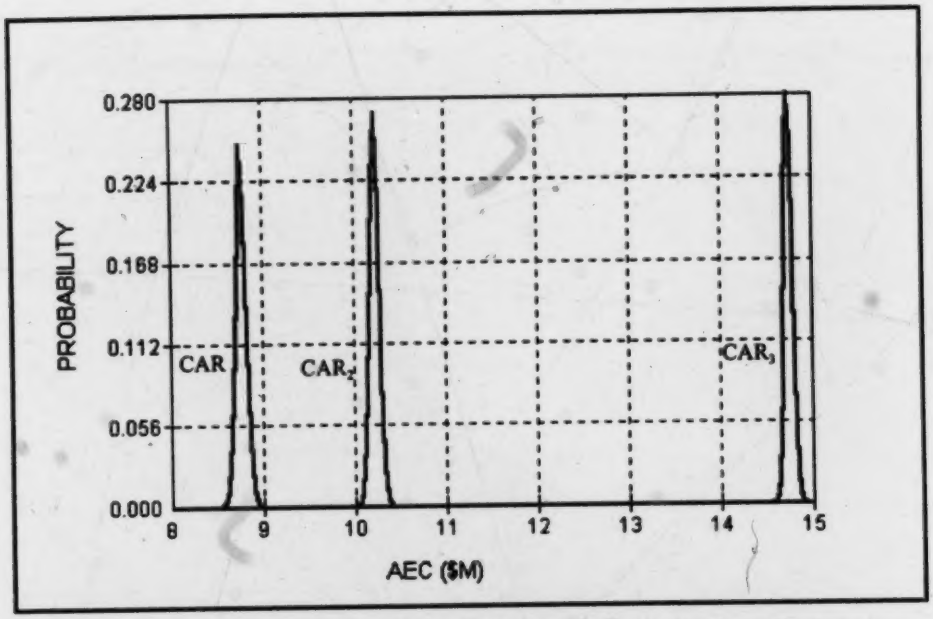


Figure 6.15: AEC Distribution For The CAR Base and Variant Options

Figure 6.16 illustrates the AEC distribution for the CAR_1 option. The AEC range is from \$8.75M to \$8.79M with a standard deviation of \$5,828.

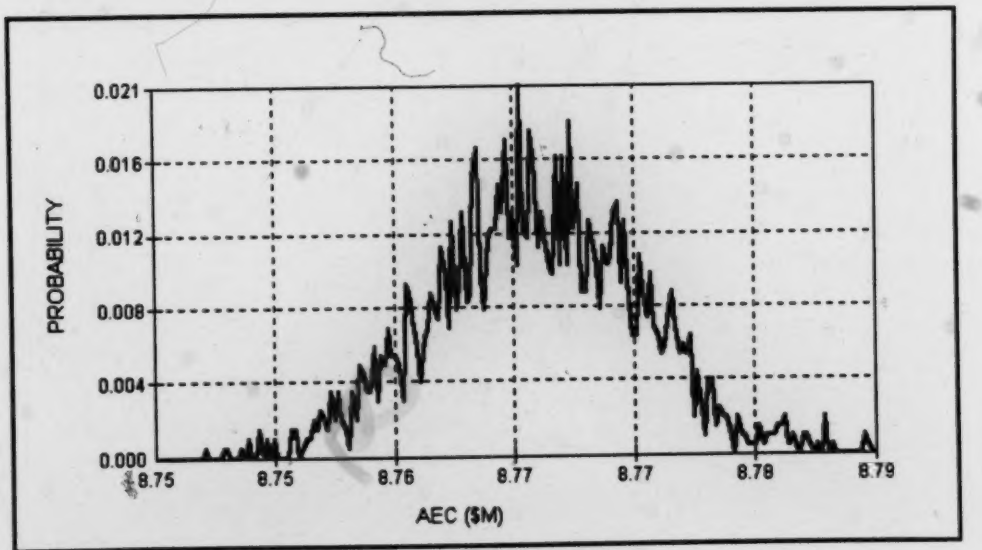


Figure 6.16: AEC Distribution For The CAR_1 Option

The expected AEC for the base CAR and its variant options, CAR_1, CAR_2, and CAR_3 when expressed per unit of output, easily conveys the varying levels of expenditure necessary to achieve Hospital A's annual target number of MRI exams. Figure 6.17 illustrates the expected cost per MRI exam for the base CAR and its variant design options. Each option is designed to achieve the same objective (i.e., total annual number of MRI exams), however, under differing circumstances. It is evident that the choice of CAR design option determines the level of expenditure associated per MRI exam. Again, expected costs per MRI exam exhibit a rising pattern. The unit cost for implementing the base CAR option is \$708, while the unit costs for CAR_1, CAR_2, and CAR_3 are \$736, \$838, and \$1,218 respectively.

The first variant option CAR_1 may be a practical choice, if Hospital A does not have sufficient resources to pursue full implement (i.e., the CAR base option). Alternatively, Hospital A can opt to delay full implementation by either one or five years. A one year delay given denoted by CAR_2 results in a unit cost per exam equal to \$838. However, cost implications are more severe, if Hospital A chooses CAR_3 option, which is to delay full implementation by five years. Delays which extend into the future are certain to be accompanied by a changing political and economic climate.

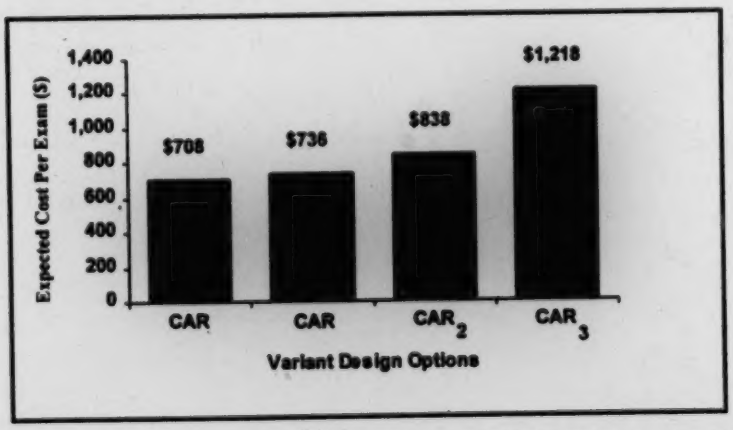


Figure 6.17: Expected Cost Per Exam For The CAR Design Options

Thus, the choice of CAR_3 must be carefully examined by decision-makers relative to the other more practical options. Figure 6.18 illustrates the percent increase in cost relative to the base option. In this figure, it can be seen that significant cost increases relative to the base option CAR are associated with CAR_2 and CAR_3 variant options. The respective percentage cost increases for CAR to CAR_1, CAR to CAR_2, and CAR to CAR_3 are about 3.95, 18.4, and 72.0 respectively. The increase in costs for these two options give rise to the existence of uncertainty in future costs. It is conceivable that in the course of delaying full implementation by one or five years, several conditions can arise which would have a significant impact in the delivery of Canadian healthcare services. As a result, estimated future costs must likely reflect changes in future political and economic climate. Decision-makers must anticipate these potential changes and factor them into their strategic policies. In fact, built-in uncertainties in estimated future costs result from using the best sources of information available today.

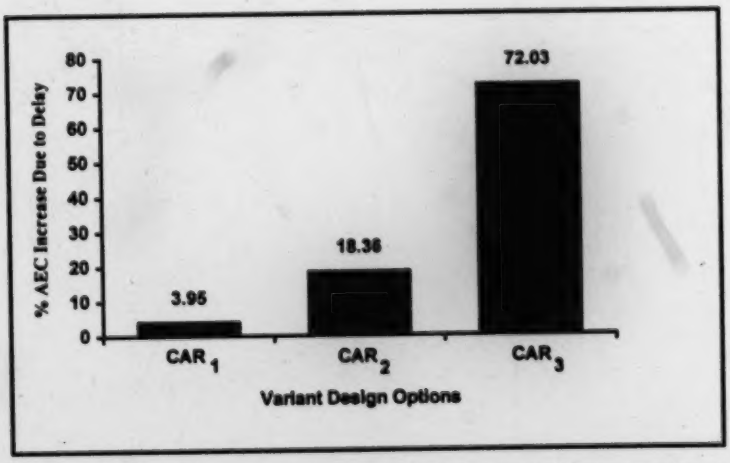


Figure 6.18: Percent Increase Due To Delay Of Base Option

Apart from the relative cost increases shown in Figure 6.18, opportunity cost represents an important element to consider in the decision-making process because it can influence the choice among CAR design options. The opportunity cost can signify savings or it can

represent losses by choosing one design option over another. Figure 6.19 illustrates the opportunity cost gained or lost by selecting a particular CAR design option.

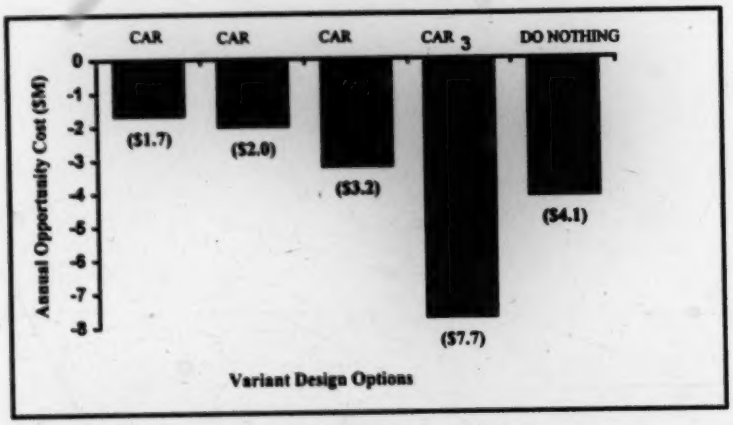


Figure 6.19: Opportunity Cost Gained (Lost) Annually

Clearly, all of the above options result in losses. Full implementation of the CAR base option or example, if Hospital A implements the base option, then it must spend $1.7M to achieve its annual target MRI exams. Hospital A faces further losses if it implements either of the variant options, which can be as high as $7.7M in CAR_3. The probability associated with achieving the expected cost for the base option, CAR, and each of its variant options CAR_1, CAR_2, and CAR_3, are displayed in Table 6.9.

Table 6.9: CAR Expected Cost Per Exam And Associated Probabilities

CAR Options	Expected Cost Per Exam	p (probability of success)
CAR	$708	49 %
CAR_1	$736	51 %
CAR_2	$838	49 %
CAR_3	$1,218	50 %

It can be seen that a 49 percent chance exists in achieving the expected cost of $708 per MRI exam which is necessary to attain the annual target number of MRI exams (i.e., using the base option CAR). Although the probabilities of success under each CAR

design option appears to be similar, there is an increasing trend in expected cost per exam. There is a noticeable increase in the expected cost between variant options CAR_2 and CAR_3. This seems reasonable due to large estimates in future costs associated with the five year delay. A risk profile illustrates the probability of failure in not achieving the estimated cost per exam. Figure 6.20 demonstrates the risk of failure associated with the CAR base and its variant options. From this figure, the probability of failure can be set so that it is fixed for the CAR base and its variant options. However, the cost per MRI exam necessary to achieve Hospital A's target varies significantly. For example, if the probability of failure is held constant at 50 percent, the expected cost per exam for CAR, CAR_2, and CAR_3 are approximately \$730, \$850, and \$1,220 respectively. The best choice among these options is CAR. The critical lower and upper limits provides additional information regarding achieving targeted outputs. The format for this analysis is structured similar to the one shown in Figure 6.21.

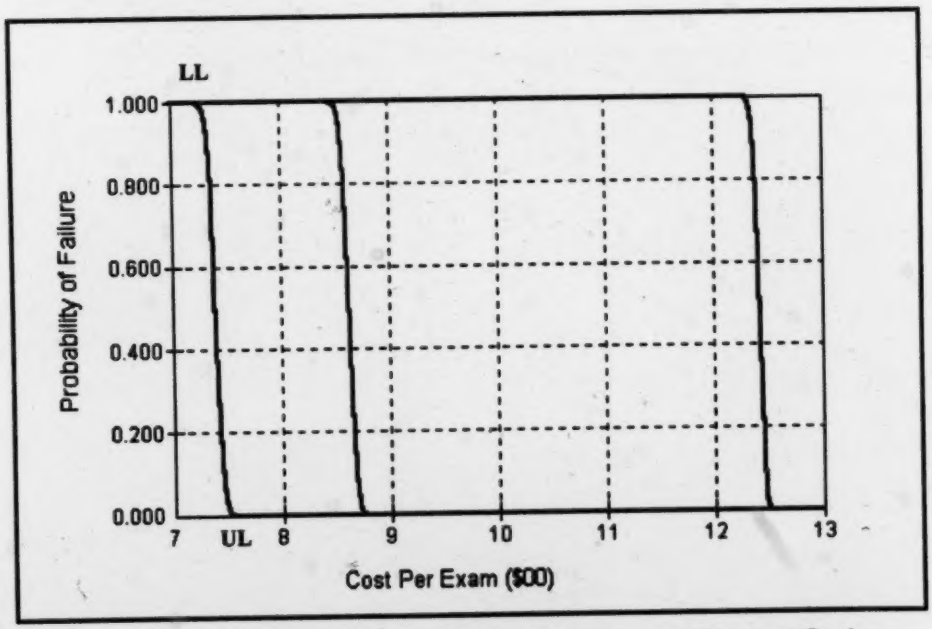


Figure 6.20: Probability of Failure For The CAR Base and Variant Option

Figure 6.21 shows an illustration of a risk profile for the CAR_1 option. The distribution for the expected cost is quite narrow. From this diagram, LL is \$734 per exam with 100 percent failure probability while UL is \$736 per exam with zero percent failure probability. In other words, a 100 percent risk of failure exists in achieving targeted outputs for the base CAR option when the expected cost per exam is at the critical lower limit. However, at the critical upper limit, there is zero chance of failure.

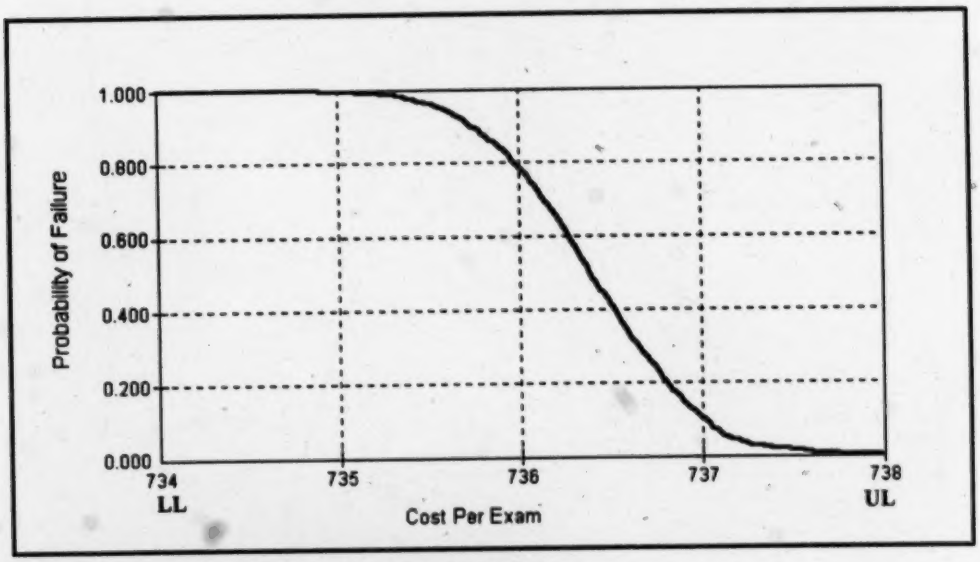


Figure 6.21: Risk of Failure For CAR_1 Option

6.4 Contract Private Operator (CPO) Design Option

The objective of this option is to permit Hospital A to achieve its annual target number of MRI exams by contracting out a specified number of MRI exams. The advantage to this option in the short-term is that Hospital A can refer its workload of MRI exams to the private operator in order to reduce its wait list. Patients would have greater access to MRI service and the cycle time for an MRI exam would be shortened significantly. In addition, Hospital A does not commit resources towards re-capitalization. Rather, it can allocate resources towards reducing its MRI exam workload during periods of high demand. The disadvantage in the long-term is that operating costs at Hospital A's MRI

system is likely to increase due to technological obsolescence, and expected frequent repairs. Furthermore, with the CPO design option, the equipment utilization rate at Hospital A remains the same (i.e., 34.7 percent). Hospital A's MRI continues to operate at 50 hours per week for a total of five days per week.

6.4.1 Functional Moment Analysis Of The CPO Base Design Option

The cost variables which define the AEC function are given in the sensitivity component analysis for the CPO design option as shown in Table 6.10. The annual equivalent cost for MRI exams is comprised of the following variables: fixed price, fixed volume, reduced price, and incremental volume. Only reduced price and incremental volume are denoted as random variables and are indicated in bold type.

Table 6.10 Sensitivity Component Analysis For The CPO Design Option

Variable	Mean	STD DEV	% BIAS	%VAR
Fixed Price	1,000	0	0.000	0.00
Fixed Volume	3,591	0	0.000	0.00
Reduce Price	750	75	0.000	50.01
Incremental Vol.	3,591	359	0.000	49.99

Total BIAS IN	AEC ($) Per Exam	0.000
Estimated Mean	AEC ($) Per Exam	753
Total STD DEV	AEC ($) Per Exam	45.63

Reduced price and incremental volume explains 50.01 percent and 49.99 percent respectively of the total variation in the AEC for the CPO design option. Both random variables exhibit equal influences on the AEC for the base CPO option. Reduced price is an incentive given by the private operator to Hospital A for every MRI exam performed beyond the fixed number set out in the contract. Incremental volume denotes the number of MRI exams performed beyond the fixed volume as specified in the contract. Increases

in the random variable, incremental volume, can occur as a result of rising demand for MRI exams, which in turn causes an increase in the AEC.

6.4.2 The CPO Stochastic Model Input Data

The two random variables identified by the sensitivity component analysis in section 6.4.1 are further processed and described by a normal PDF. The statistical parameters for the normal distribution include population estimates for the mean and standard deviation. The coefficient of variation is approximately ten percent. Thus, the standard deviation used in this option is expressed as 10 percent of the mean. The fitted input distributions along with a table summarizing the statistical parameters of the PDFs are provided in Appendix V.

6.4.3 Stochastic Simulation Results of the CPO Design Option

The fitted PDFs described in section 6.4.2 serve as inputs to the stochastic simulation model which is used in quantifying risk and uncertainty associated with the AEC function for the CPO design option. The results from the stochastic simulation model of the CPO design option for the CPO base and variant options are shown in Table 6.11.

Table 6.11: Summary Statistics of The CPO Design Option

Options	Minimum	Maximum	Mean	Std_Dev	Variance
CPO	8,037,118	9,956,876	8,955,040	270,182	7.3E+10
CPO_1	9,734,114	10,333,710	10,039,340	95,047	8.5E+09
CPO_2	9,628,769	12,303,030	10,756,330	395,406	1.6E+11
CPO_3	14,423,720	16,550,720	15,350,580	317,718	1.0E+11

From this table, there is an increasing trend in the AEC function. Under the base option CPO, Hospital A must spend $8.96 million annually to achieve its annual target number of MRI exams. However, if Hospital A implements the third variant option, CPO_3, it must spend at an even higher level to achieve the same results. It is evident that each

CPO design option is governed by a specific cost structure which decision-makers must carefully examine before adopting a particular design option.

Figure 6.22 illustrates the AEC distribution for the CPO base and variant options. The AEC distributions for CPO, CPO_2, and CPO_3 appear reasonably symmetrical except for CPO_1. The first variant option, CPO_1, has a relatively narrow distribution because its cost structure and does not vary significantly from the base case, CPO. As a result, it is plotted separately in Figure 6.23. The AEC range for CPO is from \$8M to \$10M, \$9.6M to \$12.3M for CPO_2 and \$14.4M to \$16.6M for CPO_3.

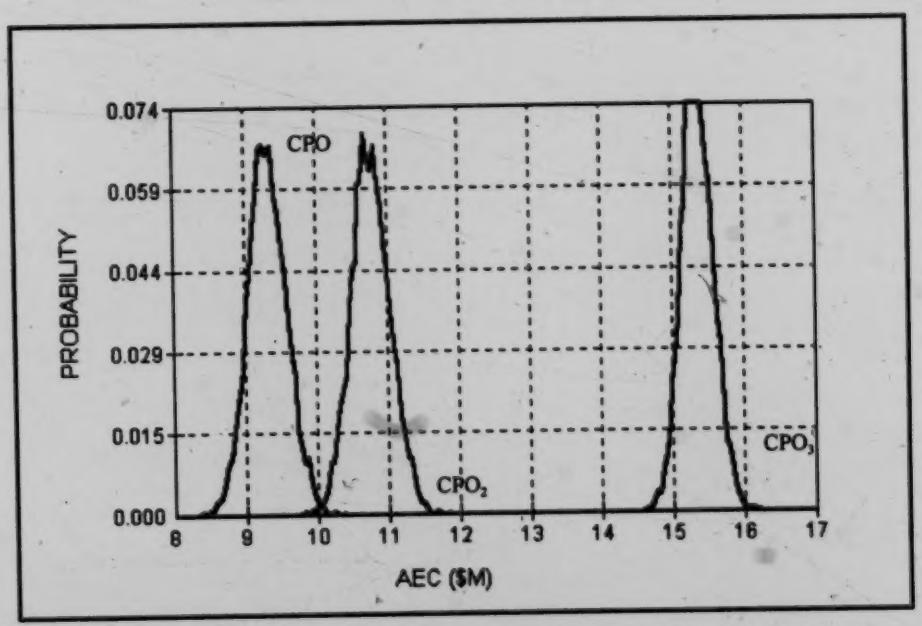


Figure 6.22: AEC Distribution For The CPO Base and Variant Options

Figure 6.23 shows an illustration of the AEC distribution for the CPO_1 option. The distribution appears reasonably symmetrical and bell-shaped. The AEC range is from \$9.7M to \$10.3 with an expected value of approximately \$10M.

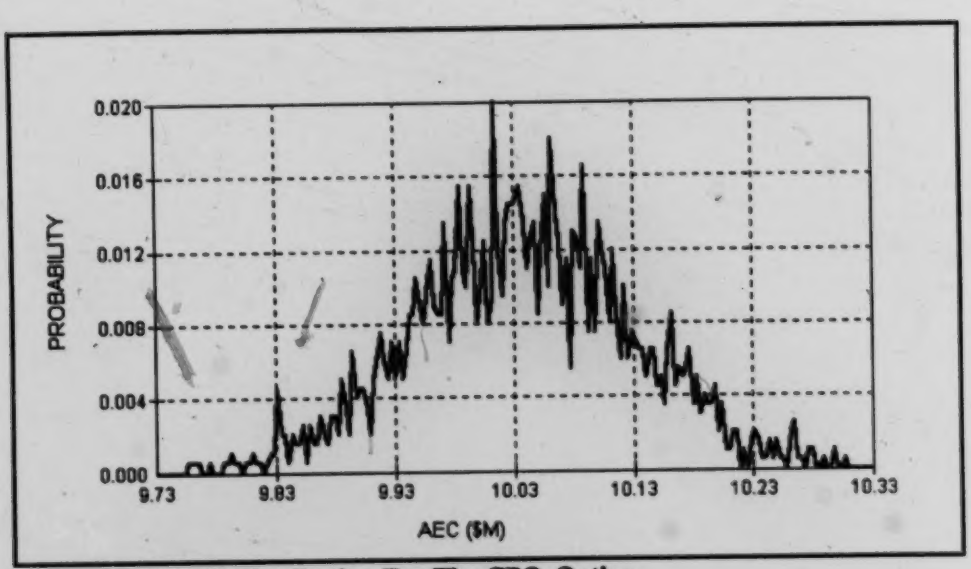


Figure 6.23: AEC Distribution For The CPO_1 Option

The expected AEC for the base and its variant options when expressed per unit of output easily conveys the varying levels of expenditure necessary to achieve Hospital A's annual target number of MRI exams. Figure 6.24 illustrates the expected cost per MRI exam for the CPO base option along with its variant options. Each option is designed to achieve the same objective, however, under differing circumstances.

From Figure 6.24, the most cost effective option is the base CPO base option at $753 per unit of exam followed by $843, $903, and $1,289 for CPO_1, CPO_2 and CPO_3 respectively. Significant increases in expected cost per unit of exam is associated with delay of fully implementing the base CPO option. Increases is cost can be attributed to the same factors described in Section 6.1.3. A useful analysis is to compare cost increases in each of the variant options relative to the base option. This comparison is useful because it clearly demonstrates the financial implications of selecting a particular design option.

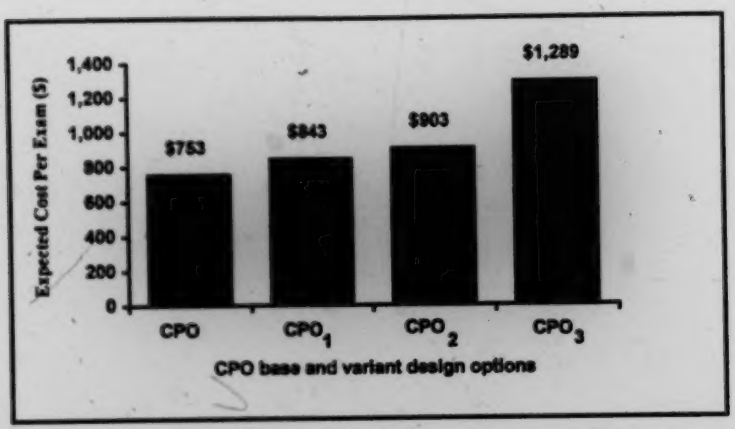


Figure 6.24: Expected Cost Per Exam For The CPO Design Options

Figure 6.25 illustrates the percent increase in cost relative to the base option. Significant cost increases relative to the base CPO option is identified with variant options CPO_2 and especially CPO_3. The respective percentage cost increases for CPO to CPO_1, CPO to CPO_2, and CPO to CPO_3 are about 12.0, 19.9, and 71.2 respectively. The increase in costs for these two options give rise to the existence of uncertainty in future costs. It is conceivable that in the course of delaying full implementation by one or five years, several conditions can arise which can have a significant impact on the future political and economic climate.

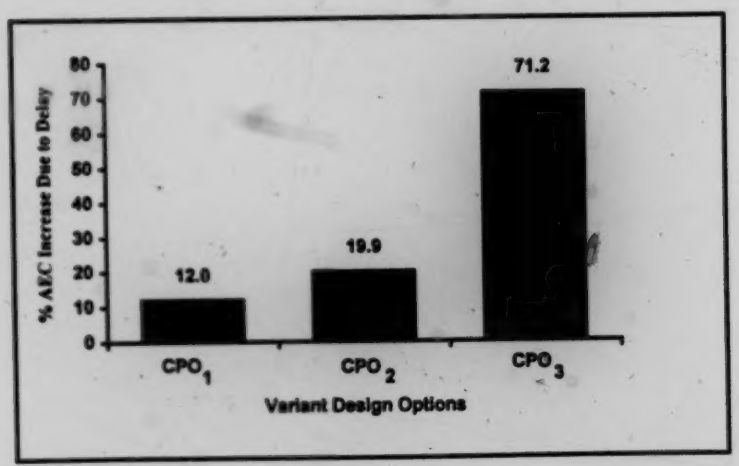


Figure 6.25: Percent Increase Due To Delay Of Base Option

For example, it is possible that privatization might play an increasing role in the delivery of health services which would give rise to the market place dictating the price for an MRI exam. If this is the case, then future prices for an MRI exam conducted by a private operator may be much higher, especially if the level of demand rises. Such uncertainty in future prices are likely to affect Hospital A's ability to achieve its annual target of MRI exams.

The opportunity cost represents an important element to consider in the decision-making process because it can influence the choice among CPO design options. The opportunity cost can signify savings or it can represent losses by choosing one design option over another. Figure 6.26 illustrates the opportunity cost gained or lost by selecting a particular CPO design option.

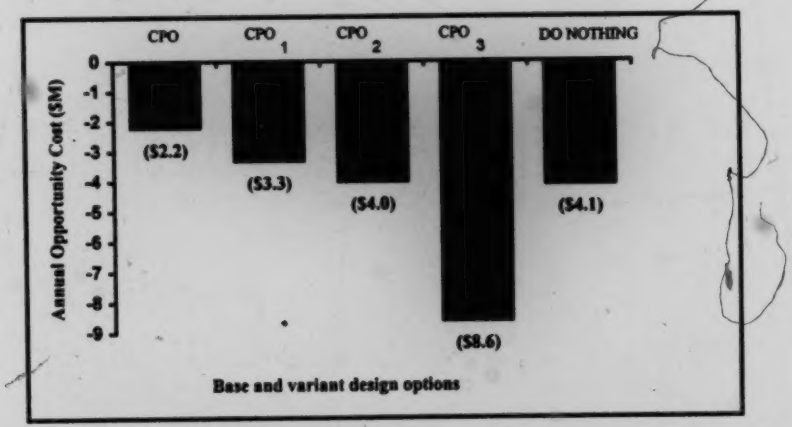


Figure 6.26: Opportunity Cost Gained (Lost) Annually

Figure 6.26 shows that losses are experienced by all of the design options. The most significant loss which amounts to $8.6 million annually is associated with the third variant option CPO_3, whereas the loss directed at the CPO base option is the least at $2.2 million. If Hospital A selects the CPO base option, then they must provide an additional $2.2 million annually to achieve the health region's annual target number of MRI exams. Further delaying full implementation of the CPO base option results in a trend of

increased losses as illustrated in this figure. One plausible explanation surrounding these losses can be attributed to the private operator's profit margin base. The extent of the profit margin base can only be estimated as there is insufficient information to arrive at a reasonable assessment. The probability associated with achieving the expected cost for the CPO base option and each of its variant options are displayed in Table 6.10.

Table 6.12: CPO Expected Cost Per Exam and Associated Probabilities

CPO Options	Expected Cost Per Exam	p (probability of success)
CPO	$753	50 %
CPO_1	$843	50 %
CPO_2	$903	51 %
CPO_3	$1,289	51 %

It can be seen that a 50 percent chance exists in achieving the expected cost of $753 per MRI exam which is necessary to attain the annual target number of MRI exams (i.e., 11,907). If decision-makers select the first variant option CPO_1, then they must be willing to spend $843 per MRI exam to attain the same probability of success as the base option. Although the probabilities among the CPO design options are similar as shown in Table 6.10, each is achieved at a different cost structure. A risk profile illustrates the risk of not achieving the estimated cost per exam. Figure 6.27 demonstrates the risk of failure associated with the CPO base option and its variant options.

From Figure 6.27, the critical lower limit for CPO, CPO_2, and CPO_3 are $675, $807, and $1,211 respectively. The critical upper limit for CPO, CPO_2, and CPO_3 are $836, $1,033, and $1,340 respectively. At the lower limit, there is a 100 percent chance of failing to meet targeted objectives, whereas, a zero percent probability of failure exists in achieving objectives at the upper limit. Unfortunately, spending at the upper limit is extreme and certainly uneconomical for CPO_2 and CPO_3 as compared to the base option, CPO. However, under-spending at the lower limit is disastrous because it guarantees failure. Thus, an acceptable level of risk must be carefully and strategically determined.

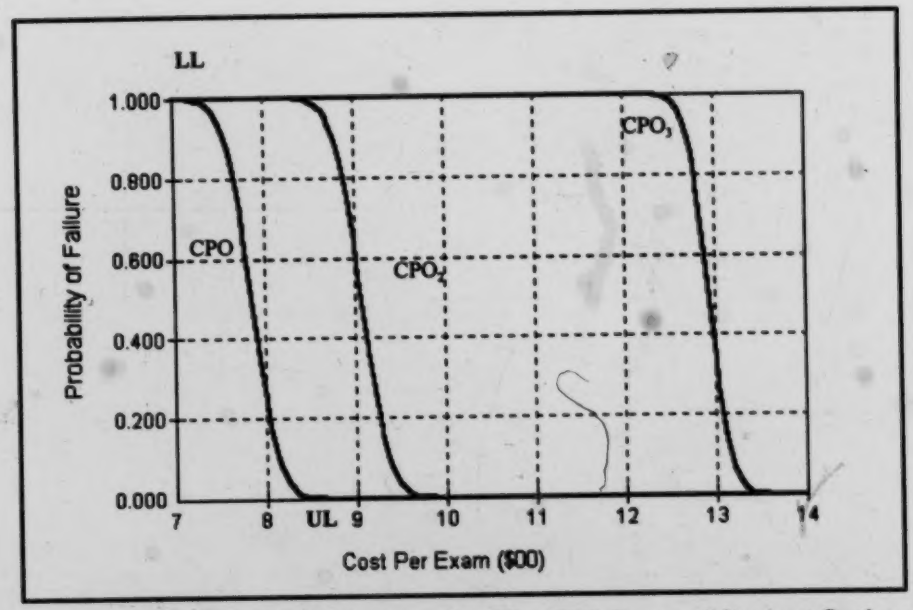


Figure 6.27: Probability of Failure For The CPO Base and Variant Options

Figure 6.28 illustrates the probability of failure for the CPO_1 option. From this figure, a 100 percent risk of failure exists in achieving targeted outputs when LL is $820 per exam. However, at UL, there is no chance of failure when the cost per exam is $870. It is uneconomical to spend at the upper limit mark, however, spending at the lower limit creates additional problems such as increases to the wait list. From Table 6.10, Hospital A is willing to assume a 50 percent chance of failing to achieve its annual target at an expected cost per exam equal to $753.

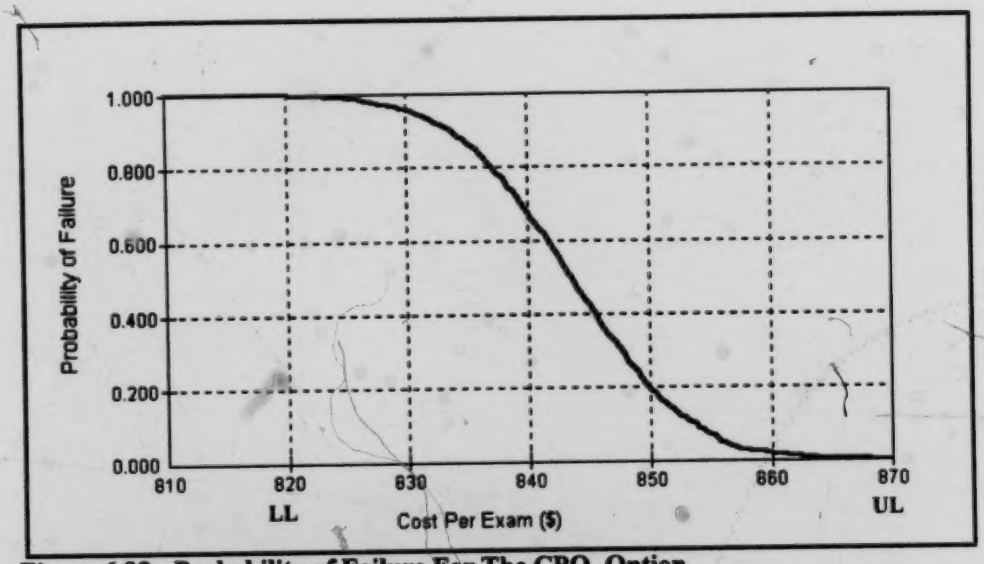


Figure 6.28: Probability of Failure For The CPO_1 Option

6.5 Lease Capital Equipment (LCE) Design Options

The objective of the LCE option is to permit Hospital A to achieve its annual target number of MRI exams by leasing its capital equipment requirements instead of outright purchase. Leasing is used to finance the purchase of hardware and software components necessary to upgrade Hospital A's MRI operation. A 1.5T (Tesla) MRI is leased together with a smaller 0.25T equipment. The addition of these two MRIs ensures that Hospital A can expand and thereby provide a variety of services not previously possible with the existing setup. For instance, the smaller 0.25T machine enables Hospital A to support interventional MRI, pediatric MRI, and orthopedic MRI.

The advantage in the short-term is that the LCE option is an attractive method of financing the MRI equipment at Hospital A. With the LCE option, Hospital A can preserve its capital budget and use it to finance purchases of less expensive, smaller capital equipment requests. The wait list is expected to decrease appreciably, while patient access is likely to improve dramatically thereby enhancing the quality of delivered services. Also, the LCE option enables Hospital A to acquire new technology with a buyout option at the end of the lease. The buyout option transfers the risk of equipment

obsolescence to the lessor (equipment owner). If Hospital A elects not to exercise the buyout option, the lessee (Hospital A) can return the equipment to the lessor at the end of the lease. The lease contract between Hospital A and the vendor is a capital lease which includes a cancellation clause. A cancellation clause is useful, especially if future demand for MRI services decreases. An advantage to a cancellation clause is that it does not penalize Hospital A for terminating the lease contract before its expiry date.

Upgrading the existing MRI system ensures that operating hours are increased from 50 to 126 hours per week. At this rate, the MRI wait list would be more manageable, and not altogether abolished because the current demand is artificial as pointed out earlier. The operation extends from five to seven days per week. Labor would increase from 3.3 full-time equivalents (FTE) to 5.5 FTEs in order to manage higher patient throughput. Also, with increased operating hours, equipment utilization is expected to increase from 34.7 to 87.5 percent. Thus, the short-term effects from implementing the LCE design option results in decreased capital cost. However, in the long-term, operating and especially maintenance costs are expected to decrease. Unfortunately, annual lease payments are excessive in the long-term.

6.5.1 Functional Moment Analysis Of The LCE Base Design Option

The cost variables associated with defining the annual equivalent cost (AEC) function for the LCE option is given in the sensitivity component analysis shown in Table 6.11. The results indicate that that seven random variables shown in bold type, contribute towards explaining the total variance of the AEC function for the LCE design option. Details of the results from sensitivity component analysis for the LCE design option is the same as those presented in the UES design option found in Section 6.1.1. The major difference between these two design options is that the lease payment replaces the capital cost. Otherwise, the unit cost variables are the same. Refer to Section 6.1.1 to avoid repetition for the interpretation of the results from the sensitivity component analysis.

6.5.2 The LCE Stochastic Model Input Data

The seven random variables identified in section 6.5.1 are further processed and fitted with probability distribution functions (PDF) using the Bestfit software package described in Chapter 5.0. The fitted PDFs for the LCE design option are the same as those described in Section 6.1.2 because the numerical value for random unit cost variables are the same. Again, refer to section 6.1.2 to avoid repetition for the interpretation of the results for the LCE design option.

6.5.3 Stochastic Simulation Model of the LCE Design Option

The fitted input distributions described in section 6.5.2 are used as inputs to the stochastic simulation model to assist with quantifying risk, and uncertainty associated with the AEC function for the LCE design option. The results from the stochastic simulation model include the LCE base and variant options as shown in Table 6.12.

Table 6.13 Sensitivity Component Analysis For The LCE Design Option

Variable	Mean	STD DEV	% BIAS	%VAR
Medfee	1,190,700	156,334	0.000	40.48
Medsal	60,011	6,001	0.000	0.06
Relstaff	64,417	19,003	0.000	0.60
Prepay	20,158	0.0000	0.000	0.00
Regest	563,082	187,506	0.000	57.19
Admin	71,561	0.0000	0.000	0.00
Empben	91,565	0.0000	0.000	0.00
Medsurg	5,799	580	0.000	0.00
Conmed	103,959	10,396	0.000	0.23
Drugs	10,474	1,047	0.000	0.01
Radiology	130,501	26,100	0.000	1.45
Conmain	176,819	0.0000	0.000	0.00
Other_supp	71,945	0.0000	0.000	0.00
Fixed	582,014	0.0000	0.000	0.00
Lease Payment	1,020,000	0.0000	0.000	0.00

Total BIAS IN	AEC ($) Per Exam	0.000
Estimated Mean	AEC ($) Per Exam	365
Total STD DEV	AEC ($) Per Exam	21.9

Table 6.14: Summary Statistics of The LCE Design Option

Options	Minimum	Maximum	Mean	Std_Dev	Variance
LCE	3,574,093	5,645,541	4,343,215	268,759	7.2E+10
LCE_1	4,772,890	5,197,427	4,950,731	56,275	3.2E+09
LCE_2	5,428,059	7,017,627	6,113,642	252,190	6.4E+10
LCE_3	11,166,470	12,877,140	11,791,540	190,061	3.6E+10

From Table 6.12, it can be seen that the expected AEC for the LCE base option is $4,343,215 with a standard deviation equal to $268,759. The MRI operation under the base option would generate expenditures at the expected value each year over the next five years. At this level of expenditures, Hospital A can achieve its annual target number of MRI exams equal to 11,907. By observation, a steady increase in the AEC for the LCE base and variant options is identified. The choice of one option over another can have severe cost implications as demonstrated by LCE_3. It would be uneconomical for decision-makers to consider implementing the LCE_3 variant option, when a more practical choice might be to pursue implementing the LCE base option. Figure 6.29 illustrates that the AEC distribution for the LCE base and variant options.

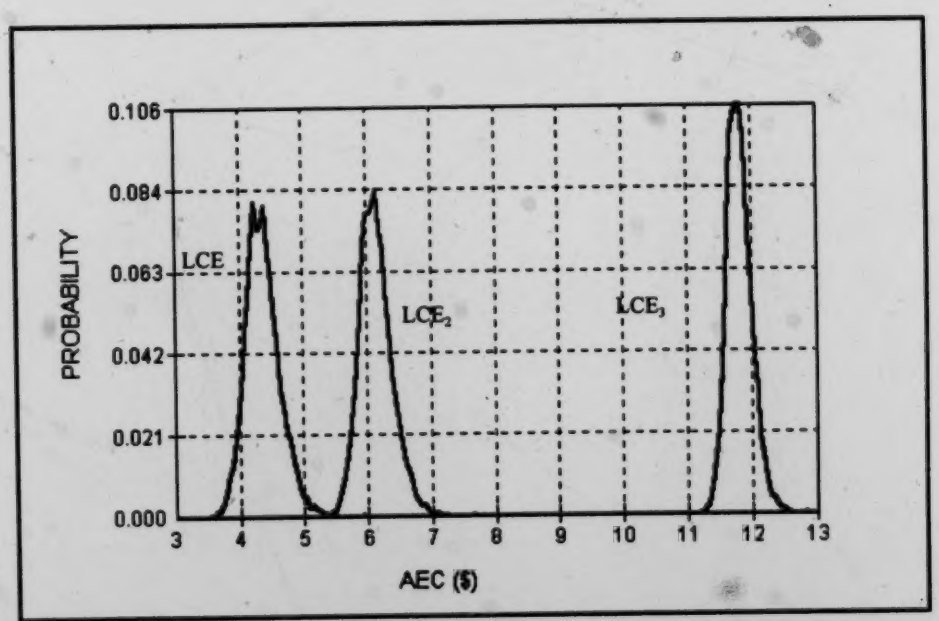


Figure 6.29: AEC Distribution For The LCE Base and Variant Options

The AEC cost is greatest for the third variant option, LCE_3, which has a range from $11.2M to $11.8M. The most cost effective option is given by LCE which has as a range from $3.6M to $5.5M. Clearly, the choice of LCE option remains a management decision. However, consideration must be given to the uncertainty of future costs

because estimates of these costs are generated from today's data. It is very possible that lease rates can change significantly in one and even more drastically in five years, if the LCE_2 and LCE_3 are selected respectively. Several factors can influence increase in lease rates. For example, rapid changes in technology can result in escalating costs, especially critical for the MRI system because of its dependency on sophisticated computer hardware and software components.

A closer examination of the AEC distribution for the LCE_1 option is illustrated in Figure 6.30. The AEC range is from \$4.8M to \$5.2M. There appears to be little variability in the values shown for the AEC distribution which implies a low degree of risk associated with the LCE_1 option. The AEC when expressed per unit of output, clearly shows this increasing trend in cost among the LCE design options. Figure 6.32 illustrates the expected cost per exam for the LCE base option and the three variant design options LCE_1, LCE_2, and LCE_3.

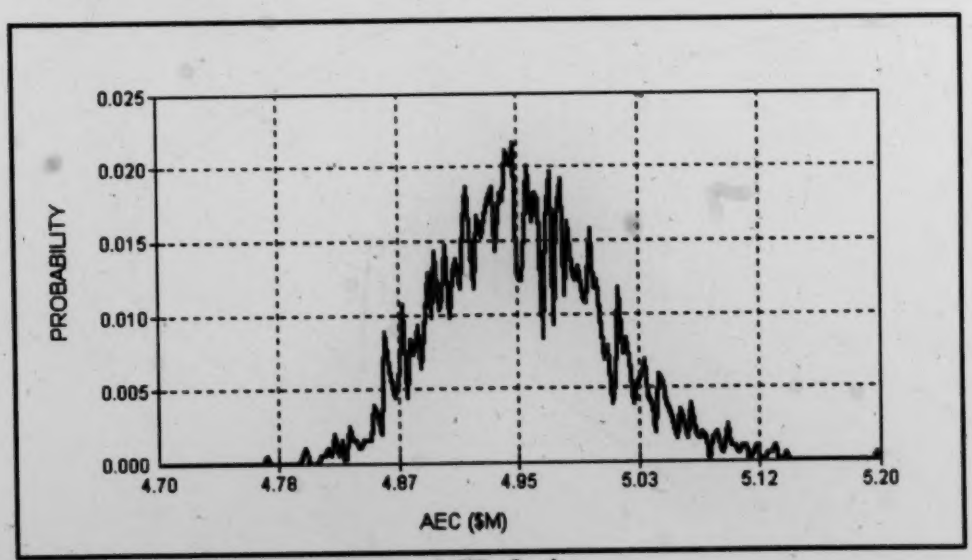


Figure 6.30: AEC Distribution For LCE_1 Option

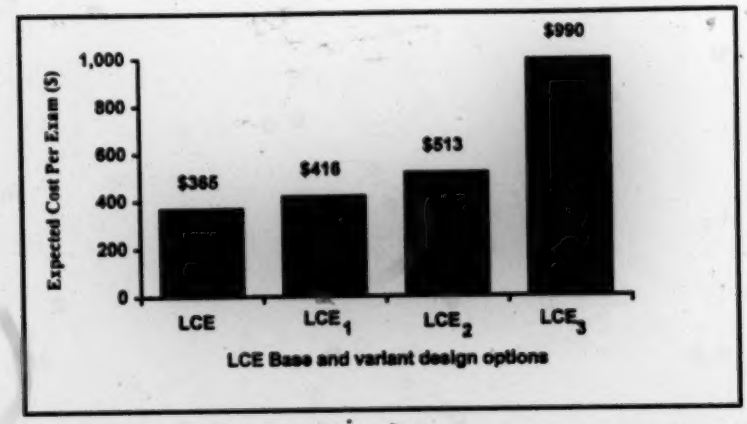


Figure 6.31: Expected Cost Per Exam For The LCE Design Option

From this figure, it is evident that selecting the base design option is more cost effective when compared to the three variant options. For instance, by implementing the base option today, Hospital A can assure itself of achieving its targeted annual MRI exams at a cost of $365 per exam. However, delaying implementation of the LCE base option can result in significant cost increases. For instance, increases in cost can be attributed to changes in technology which affects both the MRI hardware and software components. It is unlikely that Hospital A will continue to lease the same MRI equipment for five years because technological advancement will render the equipment obsolete. Therefore, it is reasonable to expect Hospital A to lease new MRI equipment, for instance, after year three of its five year contract to avoid rising operating costs. Decisions surrounding replacement of leased MRI equipment must be made by carefully monitoring operating cost curves. Obviously, it is uneconomical to retain leased equipment with costs rising up along the operating cost curves. Replacement of leased equipment must be part of the overall capital equipment strategic planning process. The economic implications among the various LCE design options become clear when comparing the variant options to the LCE base option. Figure 6.32 illustrates the percent increase in cost relative to the LCE base option.

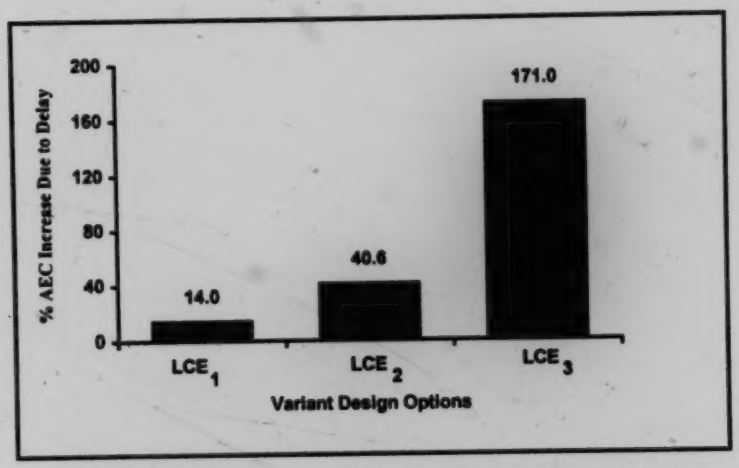


Figure 6.32: Percent Increase Due To Delay Of Base Option

The respective percentage cost increases for LCE to LCE_1, LCE to LCE_2, and LCE to LCE_3 are about 14, 40.6 and 171 respectively. It is clear from this figure that the most appropriate choice is LCE_1. While Figure 6.33 shows the relative cost increases associated with each variant design option, it does not convey the opportunity cost forgone by selecting a particular LCE variant option. The opportunity cost associated with the base and variant options are illustrated in Figure 6.33. The magnitude of the opportunity cost is a function lost production, cost of financing, and escalating production costs which include rising labor and material costs. Delay of full implementation, which is associated with LCE_2 and LCE_3 variant options have significant compounding effects on the AEC function. From this figure, the LCE base option presents the greatest opportunity cost savings for Hospital A, if it chooses to fully implement the base option today. By fully implementing the LCE base design option today, Hospital A can experience a total savings of $2.6M annually. Otherwise, further delays only serve to erode these savings. Savings can be reinvested to improve services in other departments found in Hospital A. In fact, delaying full implementation by five years as indicated by the third variant option, LCE_3 results in a staggering loss amounting to $5.0M annually. In other words, Hospital A must spend an additional $5.0M above the existing cost

structure to achieve its annual target MRI exams. The do nothing option results in losses totaling $4.1M.

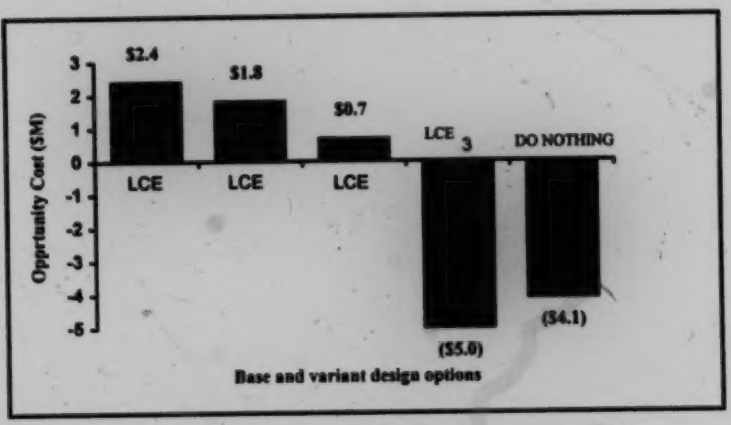


Figure 6.33: Opportunity Cost Gained (Lost) Annually

Another important element for decision-makers to consider is risk of failure. Risk of failure provides a probabilistic measure of not achieving the expected estimated cost of providing an MRI exam. Table 6.15 lists the expected estimated cost per MRI exam and its associated probability of success for each LCE design option.

Table 6.15 LCE Expected Cost Per Exam and Associated Probabilities

Options	Expected Cost Per Exam	p (probability of success)
LCE	$365	51 %
LCE_1	$416	52 %
LCE_2	$513	54 %
LCE_3	$990	52 %

The probability of success is defined as the probable outcome of achieving the estimated cost per MRI exam for the target annual MRI exams. For instance, there is a 51 percent chance of attaining an estimated cost of $365 per MRI exam for the LCE base option. Unfortunately, these probability values do not convey sufficient information about the risk of failure which is important in this study. Instead, what is needed is a risk profile

which is useful for providing a range of probable outcomes so that decision-makers can carefully assess potential risk of failure associated with each estimated cost per exam. Figure 6.34 illustrates the risk profiles for all of the LCE design options, while Figure 6.35 illustrates a risk profile for the LCE_1 option.

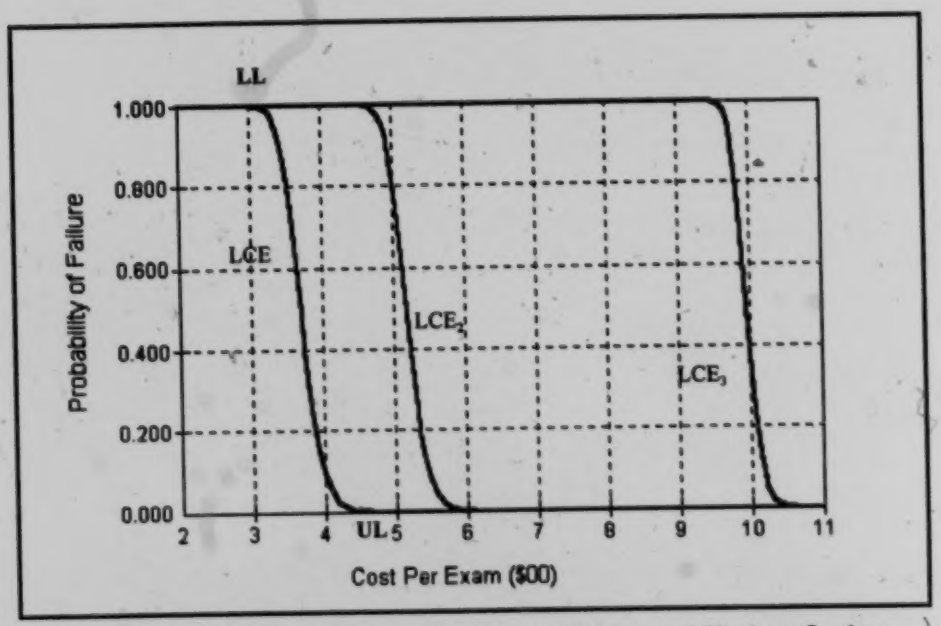


Figure 6.34: Probability of Failure For The LCE Base and Variant Options

From Figure 6.34, a comparison among the LCE design options are presented along with their associated probabilities. The advantage in presenting the probability failure curves in this format is to allow decision-makers to observe the cost effect by varying the level of probabilities. As the probability of failure increases, the cost per MRI exam decreases. In other words, Hospital A can minimize costs by accepting a higher level of risk. However, there is a possibility that a selected cost structure would not meet its targeted outputs. The obvious choice is to select a lower level of risk. Unfortunately, such a decision leads to a high cost per exam which requires Hospital A to commit to over-spending. Again, the critical lower and upper limits define the probability of 100 percent failure rate, and the probability of zero percent chance of failure respectively.

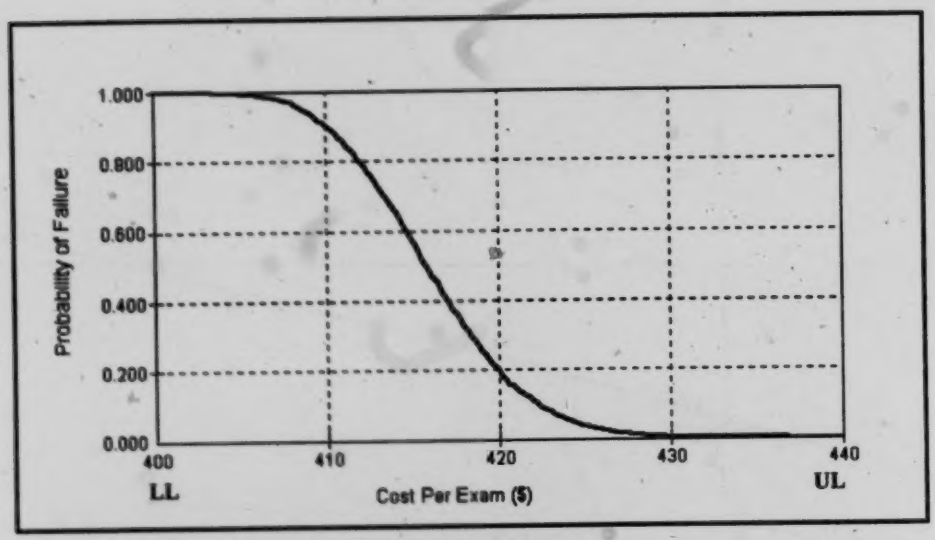


Figure 6.35: Risk of Failure For the LCE_1 Option

From this figure, the lower limit, LL, is achieved at a unit cost of $400 while the upper limit, UL is reached at $436. There is a 100 percent chance of failure in achieving targeted outputs when LL is reached. At the LL mark, Hospital A is seeking an unrealistic objective, and thus, faces an impossible task in meeting the organization's objectives (i.e., attaining the annual number of MRI exams). At the other extreme, UL, Hospital A is committing to over-spending by assuming no risk at all. Unfortunately, the operating efficiencies of other subsystems are certain to suffer from such an excessive MRI cost.

6.6 Contract Another Hospital (CAH) Design Options

The objective of the CAH design option is to acquire a new 1.5T (Tesla) MRI and locate it in another tertiary care centre, known as Hospital B which is situated in Health Region A. This option would permit hospital A to achieve its annual target number of MIR exams. The short-term implication is that Hospital A does not commit resources toward retro-fitting its existing MRI operation. This means that the necessary MRI equipment upgrades are ignored in favor of a new MRI installation at Hospital B. Two fully

functional MRI systems ensures that the wait list decreases, and patient access to MRI service in Health Region A improves appreciably. Unfortunately, the long-term effect for Hospital A's MRI subsystem is increasing operating costs due to worn and obsolete parts. Operating efficiencies at both hospitals are certain to suffer because neither system is fully utilized. The MRI equipment at Hospital A would continue to operate at 34.7 percent of its rated capacity, whereas, the equipment at Hospital B is utilized only 52.8 percent of the time. In addition, Hospital B is likely to face problems in the future related to equipment upgrades, unless there is some provision for retrofitting its system.

6.6.1 Functional Moment Analysis Of The CAH Base Design Option

The cost variables associated with defining the Annual Equivalent Cost (AEC) function and the results of the sensitivity component analysis are shown in Table 6.19. It can be seen by the results shown under the %VAR column that that seven random variables contribute towards explaining the total variance of the AEC function for the CAH design option. The results from sensitivity component analysis for the CAH design option is the same as those for the UES found in section 6.1.1 because the unit cost variables are assumed to be the same. The only change in this case is the number of hours of operation. Hospital A operates its MRI system at 50 hours per week, whereas Hospital B's operation revolves around 76 hours per week to ensure that the target number of MRI in Health Region A is met. Refer to section 6.1.1 to avoid repetition for the interpretation of the results from the sensitivity component analysis.

Table 6.16 Sensitivity Component Analysis For The CAH Design Option

Variable	Mean	STD DEV	%BIAS	%VAR
Medfee	718,200	71,820	0.000	79.72
Medsal	36,197	3,620	0.000	0.20
Relstaff	38,855	3,886	0.000	0.23
Prepay	12,159	0.0000	0.000	0.00
Regest	339,637	33,964	0.000	17.83
Admin	43,164	0.0000	0.000	0.00
Empben	55,230	0.0000	0.000	0.00
Medsurg	3,498	350	0.000	0.00
Conmed	62,705	6,271	0.000	0.78
Drugs	6,318	632	0.000	0.01
Radiology	78,715	7,872	0.000	1.23
Conmain	176,819	0.0000	0.000	0.00
Other_supp	43,395	0.0000	0.000	0.00
Fixed	582,014	0.0000	0.000	0.00
Capital Cost	2,000,000	0.0000	0.000	0.00

Total BIAS IN	AEC ($) Per Exam	0.000
Estimated Mean	AEC ($) Per Exam	365
Total STD DEV	AEC ($) Per Exam	11.96

6.6.2 The CAH Stochastic Model Input Data

The seven random variables identified in Section 6.1.1 are further processed and fitted with probability distribution functions (PDF). The fitted PDFs for the CAH design option are the same as those described in Section 6.1.2 because the numerical value for random unit cost variables are the same. Again, refer to section 6.1.2 to avoid repetition for the interpretation of the results for the CAH design option.

6.6.3 Stochastic Simulation Results of the CAH Design Option

The fitted input distributions described in Section 6.6.2 are entered into the Excel spreadsheet for the stochastic simulation model to assist with quantifying risk and uncertainty associated with AEC function for the CAH design option. The results from the stochastic simulation model which includes the CAH base and its variant options shown in Table 6.17.

Table 6.17: Summary Statistics of The CAH Design Option

Options	Minimum	Maximum	Mean	Std_Dev	Variance
CAH	5,135,586	6,518,209	5,608,325	161,228	2.6E+10
CAH_1	6,094,115	6,266,073	6,172,442	23,325	5.4E+08
CAH_2	6,767,222	7,780,130	7,229,165	150,596	2.3E+10
CAH_3	12,057,380	12,889,250	12,409,260	123,027	1.5E+10

The expected cost for the CAH base and its variant design options are on an upward rise. The most cost effective option given by the base option, CAH, has a range from \$5.1M to \$6.5M with a standard deviation of \$161,228. The highest cost is associated with the third variant option, CAH_3, which has range of \$12.1M to \$12.9M with a standard deviation of \$123,027. Figure 6.36 illustrates the distribution of the AEC for the base CAH and its variant options. The significant costs are associated with CAH_2 and CAH_3 as measured by the distance from the base CAH option. The AEC distribution for CAH has a range from \$5.1M to \$6.5M, CAH_2 from \$6.8M to \$7.8M and CAH_3 from \$12.1M to \$12.9M. It is clear that significant costs are associated with delaying full implementation. The most cost effective option is the base case, CAH. Figure 6.37 illustrates the distribution for the CAH_1 option. The AEC distribution is quite symmetrical and has a range from \$6.1M to \$6.3M with an expected value of approximately \$6.2M.

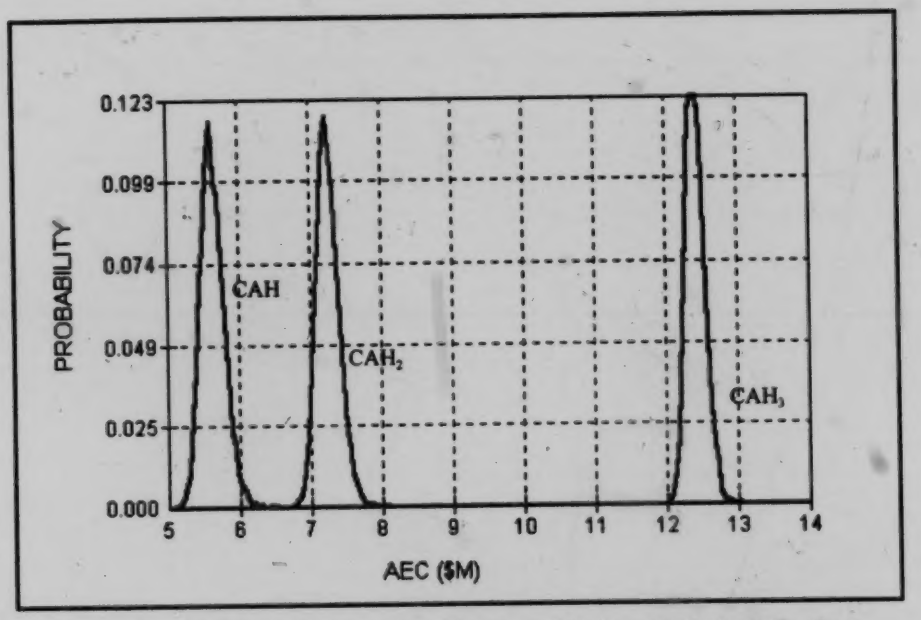


Figure 6.36: AEC Distribution For The Base CAH and Variant Options

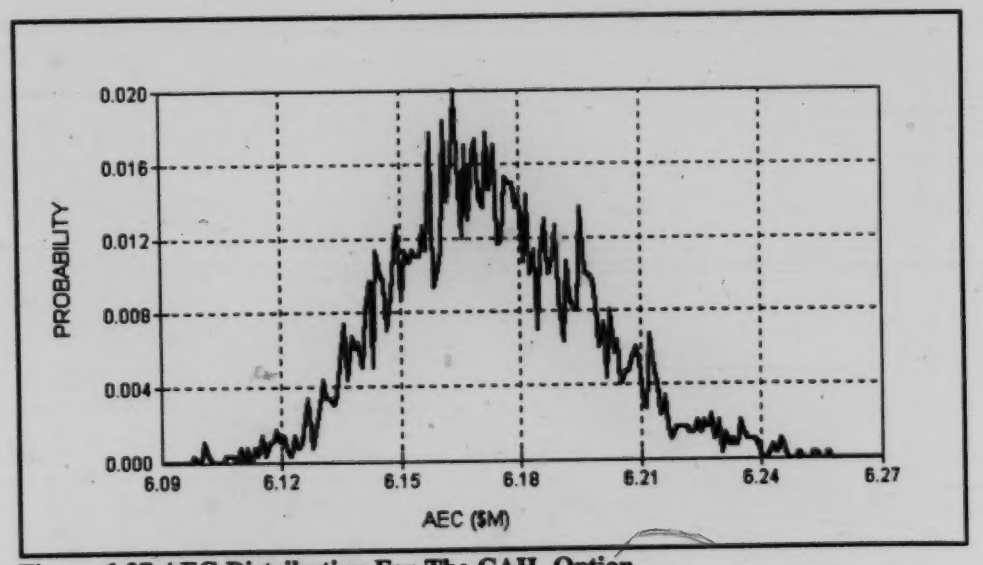


Figure 6.37 AEC Distribution For The CAH_1 Option

The results of the expected AEC for the base and variant options are more clearly understood when expressed per unit of output (i.e., exams) as illustrated in Figure 6.38.

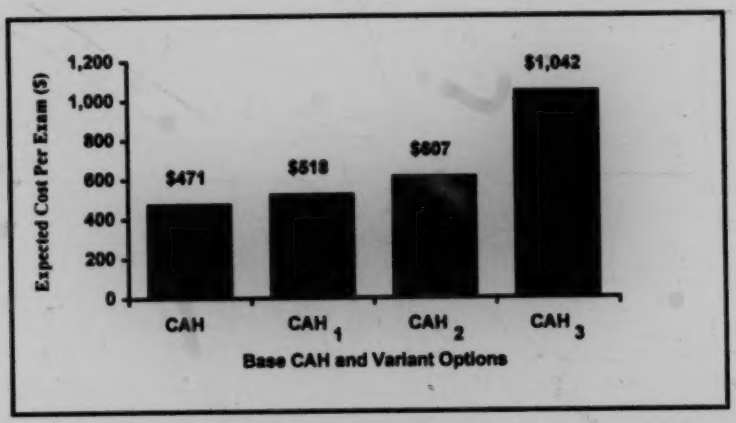


Figure 6.38: Expected Cost Per Exam For The CAH Design Options

It is apparent from this figure that the base option, CAH is more feasible when compared to the three variant design options. The Provincial Health Funding Agency can implement CAH at an expected cost per exam of $471. Alternatively, they can implement CAH_1, if resources are constrained. Otherwise, selecting CAH_2 and CAH_3 results in delaying full implementation by one and five years respectively. Unfortunately, cost implications are severe for these two options because costs in the future can change noticeably due to uncertain political and economic climates. The expected cost increases relative to the base option illustrates the financial impact associated with each of the variant options as illustrated in Figure 6.39. From this figure, severe financial implications are associated with delaying full implementation as shown by variant options, CAH_2 and especially, CAH_3. If the Provincial Health Funding Agency adopts CAH_1, then it faces a 14 percent increase in cost, otherwise, it must commit 41 and 171 percent more resources relative to the base option, if it pursues CAH_2 and CAH_3 respectively. Thus, cost increases associated with CAH_1, CAH_1, and CAH_3 are certain to erode the Provincial Health Funding Agency's capital budget, because they are

responsible for approving additional resources to hospitals, over-and-above their usual operating grants.

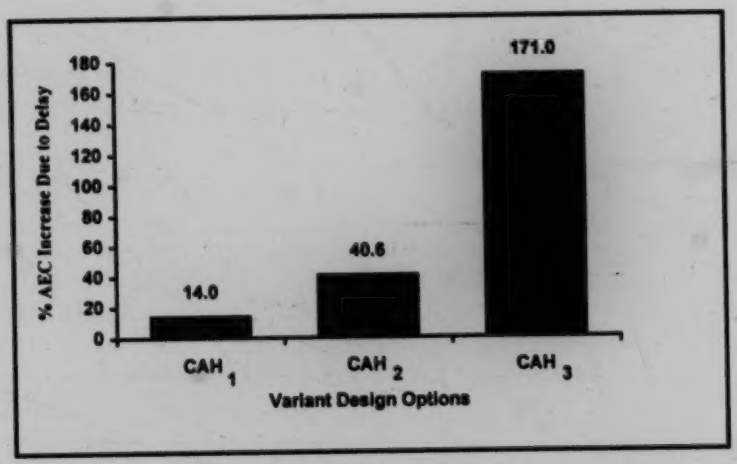


Figure 6.39: Percent Increase Due To Delay Base Option

The opportunity cost associated with the CAH base and variant options are illustrated in Figure 6.40.

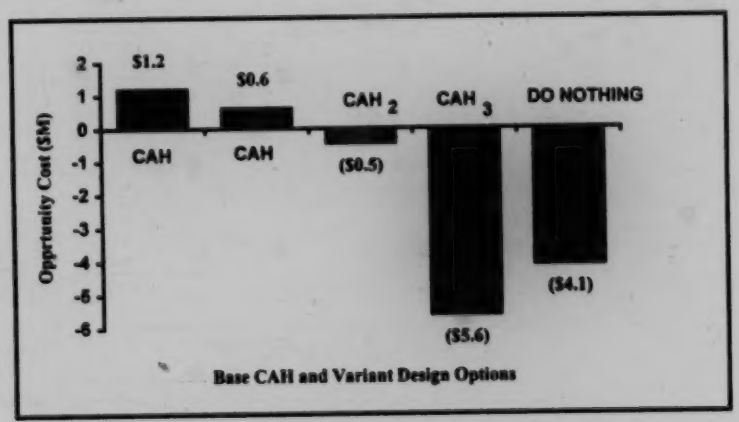


Figure 6.40: Opportunity Cost Gained (Lost) Annually

The appropriate choice from this figure is the base option, CAH because it provides the greatest savings of $1.2M, followed by CAH_1 at $0.6M. Losses comprising of $0.5M,

$5.6M, and $4.1M are associated with CAH_2, CAH_3, and the do nothing options respectively. These losses imply that the Provincial Health Funding Agency must over-spend to achieve the annual target number of MRI exams. For instance, if CAH_3 is selected, they must spend an additional 5.6M to achieve the same result as the base option, CAH. The probability of achieving the expected cost for the base and variant options is given in Table 6.18.

Table 6.18: CAH Expected Cost Per Exam and Associated Probabilities

CAH Options	Expected Cost Per Exam	p (probability of success)
CAH	$471	51 %
CAH_1	$518	52 %
CAH_2	$607	53 %
CAH_3	$1,042	52 %

The results shown in this table indicate that the probability of success are very similar among the base CAH and its variant options. However, the expected cost per exam for each option varies appreciably. For example, there is a 51 percent chance of achieving an expected cost of $471 for the base CAH option. At this level, Hospital A can achieve its annual target number of MRI exams. Unfortunately, these probability values do not convey the complete information about the risk of failure which is important in this study. Instead, what is needed is a risk profile which useful for providing a range of probable outcomes so that decision-makers can carefully assess potential risk of failure associated with each estimated cost per exam. Figure 6.41 depicts the risk profiles for the base CAH and its variant options, while a more detailed risk profile is developed for the CAH_1 option in Figure 6.42. From Figure 6.41, the risk profile for the most cost effective option is given by CAH, whereas, the risk profile for CAH_3 is associated with the most costly design option. Hospital A can achieve the same probability of failure at a lower cost structure, if they implement CAH at $471, instead of waiting five years to implement CAH_3 at a cost of $1,042.

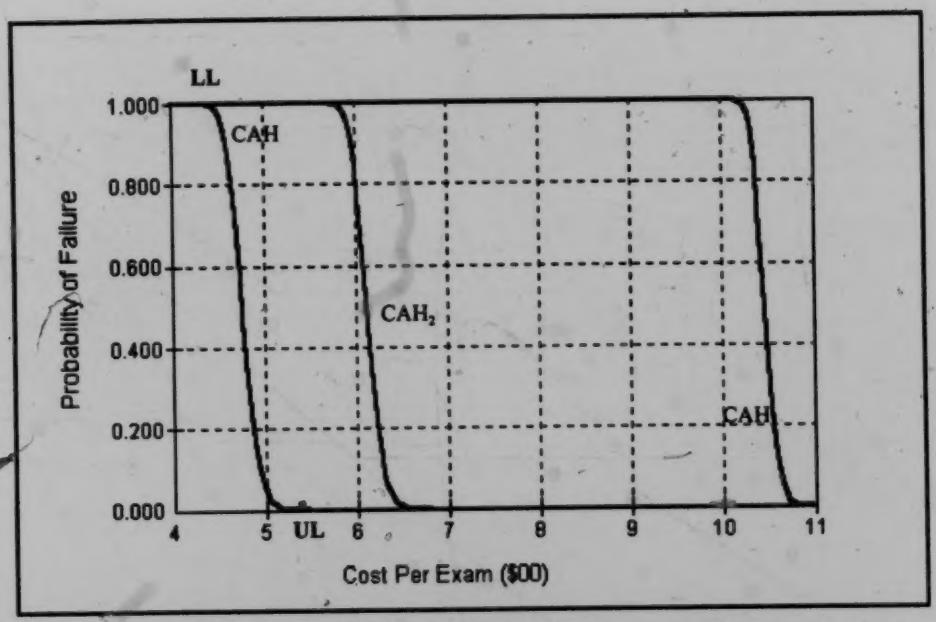


Figure 6.41: Probability of Failure For The CAH Base and Variant Options

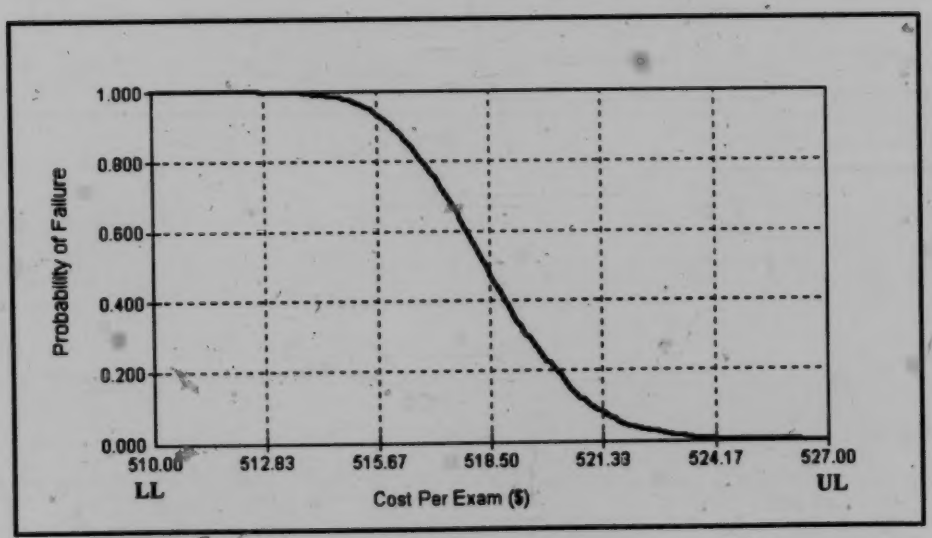


Figure 6.42: Risk of Failure For Base CAH Option

A more precise assessment of risk can be obtained by examining the cost effective option, CAH. At LL, the probability of failing to achieve targeted outputs is 100 percent. At the extreme range given by UL, there is a zero chance of failure. Unfortunately, it is uneconomical to spend at UL because resources are scarce, and therefore may not be readily available. Alternatively, at the LL mark, Hospital A is in danger of drastically increasing the size of its wait list.

6.7 Contract Mobile Operator (CMO) Design Option

The objective of this option is to contract a mobile operator to assist Hospital A in effectively reducing its workload of MRI exams annually. This option involves Hospital A contracting out its services to a mobile MRI operator. The mobile operator would be stationed on Hospital A's site and operate seven days per week for two weeks before relocating to provide services elsewhere. Essentially, the mobile operator is expected to operate 144 hours per week and thereby process a total of 272 MRI exams. Overall, the mobile operator performs 7,182 exams annually which is the proportion required so that Hospital A achieves the annual target MRI exams for Health Region A. The annual target MRI exams is achieved by combining Hospital A's throughput (i.e., 4,725) with those from the private operator to attain a total of 11,907 exams for Health Region A. Results from an MRI exam is provided within 24 hours by Radiologists stationed on the mobile unit.

In the short term, this option enables Hospital A to process MRI patients in an expedient manner and thus alleviate patients on the wait list. Hospital A would not to perform upgrades to its MRI operation. It would continue to operate at 50 hours per week, five days per week. The result is that equipment utilization remains at 34.7 percent. Unfortunately, long-term effect from this option results in Hospital A incurring higher operating and especially maintenance cost which stems from aging equipment.

6.7.1 Functional Moment Analysis Of The CMO Base Design Option

The cost variables which defines the AEC function and the sensitivity component analysis for the CMO design option are shown in Table 6.19.

Table 6.19 Sensitivity Component Analysis For The CMO Design Option

Variable	Mean	STD DEV	% BIAS	%VAR
Price	900	90	0.000	100.00
Volume	7,182	0	0.000	0.00

Total BIAS IN	AEC ($) Per Exam	0.000
Estimated Mean	AEC ($) Per Exam	767
Total STD DEV	AEC ($) Per Exam	46.5

In this option, the random variable Price explains 100 percent of the variation in the AEC for the CMO design option. Price is likely to significantly impact the expected cost per exam because it includes a number of factors. For instance, the mobile operator structures its price to include profit, charges for equipment depreciation and fixed cost variables such as insurance. They might also include contingencies for unanticipated increases in supplies such as cryogen – a liquid medium used in cooling the MRI equipment.

6.7.2 The CMO Stochastic Model Input Data

The random variable, price, identified in section 7.3.1 is described by a normal PDF. The fitted PDF and statistical parameters which describe the distribution for the random variable Price are included in Appendix V.

6.7.3 The Stochastic Simulation Results of The CMO Design Option

The fitted PDF described in section 6.7.2 is used as an input to the stochastic simulation model to assist with quantifying risk and uncertainty associated the AEC function. The

results from the stochastic simulation model of the CMO design option which includes the base and variant options are shown in Table 6.20.

Table 6.20: Summary Statistics of The AEC Function For CMO Design Option

CMO Options	Minimum	Maximum	Mean	Std_Dev	Variance
CMO	6,797,493	11,302,900	9,132,352	655,235	4.3E+11
COM_1	9,402,427	9,934,613	9,678,224	77,397	6.0E+09
COM_2	8,754,302	13,583,630	11,256,890	702,305	4.9E+11
COM_3	13,581,550	17,260,370	15,488,040	535,073	2.9E+11

The results in Table 6.20 indicate that the expected AEC increases from the base option, CMO through to the three variant options, CMO_1, CMO_2, CMO_3 respectively. The AEC for the base CMO and its variant options are illustrated in Figure 6.43, while the base CMO option is depicted in Figure 6.44. From Figure 6.45, the expected annual cost represented by the midpoint of each of the four AEC distributions shows an increasing trend. This same trend can be observed above in Table 6.20. Costs are greatest for the CMO_3 option, the most cost effective option is associated with the base option, CMO. The AEC distribution for CMO_1 appears to be narrow because only a slight shift in cost occurs relative to the base CMO option. The AEC distribution for the base CMO option presented Figure 6.46, appears reasonably symmetrical. By observation, its expected value is \$9.1M with a range from \$6.8M to \$11.3M. These findings are consistent with the results found in Table 6.20. It is often better to graphically present results because the analysis becomes more clear.

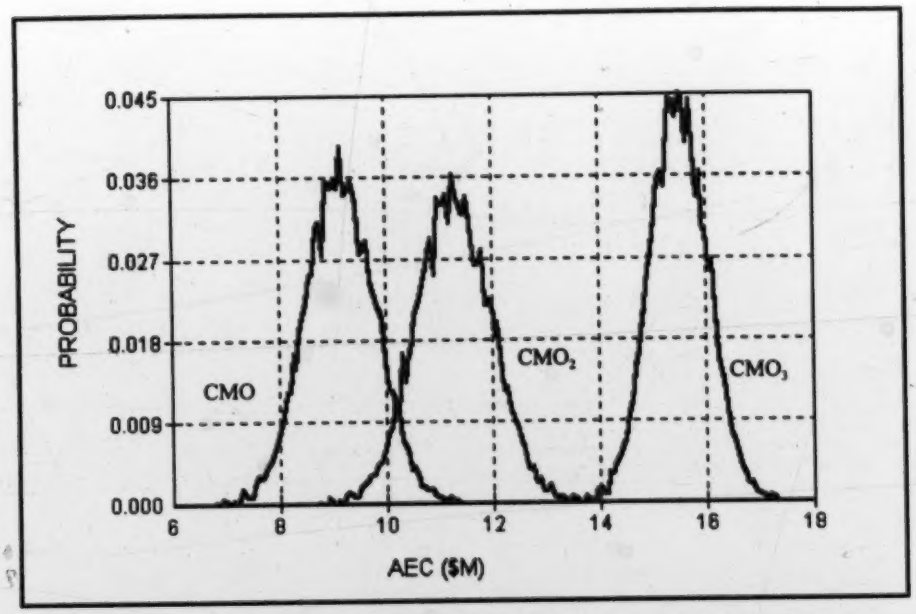


Figure 6.43: AEC Distribution For The CMO Base and Variant Options

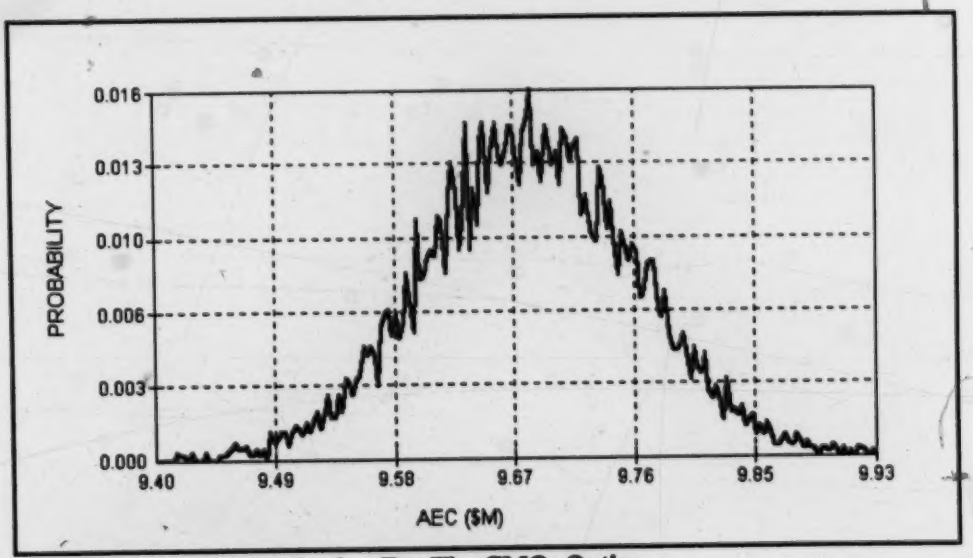


Figure 6.44: AEC Distribution For The CMO_1 Option

Figure 6.45 illustrates the cost per MRI exam for the base CMO and its variant options. It is apparent that the base CMO option is more economically feasible when compared to

the three 3 variant design options. Hospital A can implement the base CMO option where the expected cost per exam is $767. Otherwise, delays associated with CMO_1, CMO_2, and CMO_3 result in cost increases. The magnitude of these costs are attributed to escalating prices in goods and services as a result of inflation.

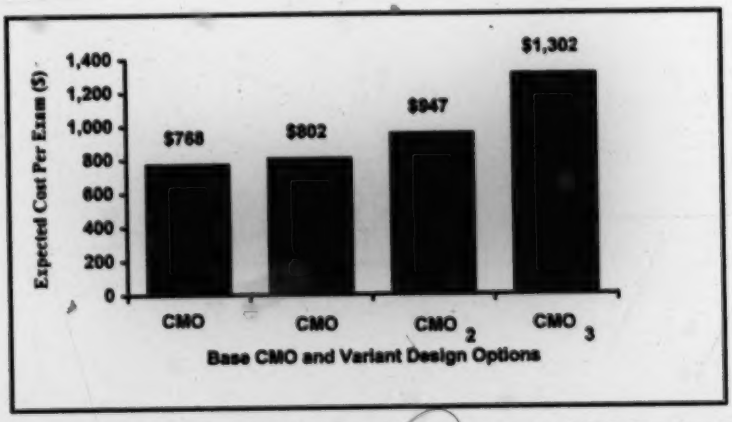


Figure 6.45: Expected Cost Per Exam For The CMO Design Options

The expected cost increases relative to the base CMO option illustrates the financial impact associated with each of the variant options as illustrated in Figure 6.46.

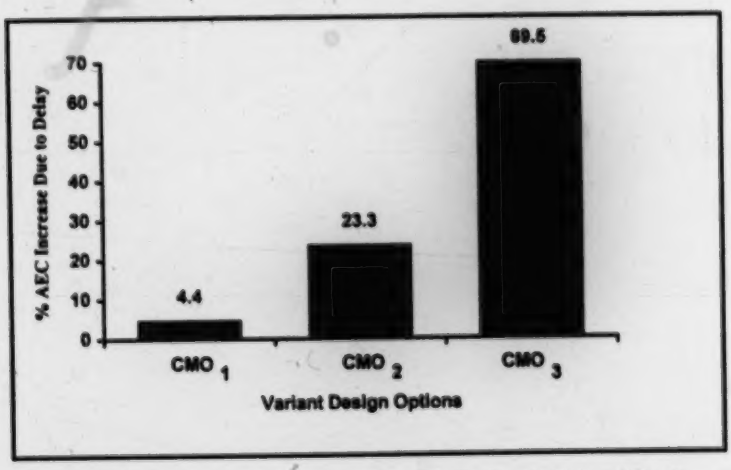


Figure 6.46: Percent Increase Due To Delay Of Base Option

From Figure 6.46, the respective percentage cost increases for CMO to CMO_1, CMO to CMO_2, and CMO to CMO_3 are about 4.4, 23.3, and 69.5 respectively. Severe financial implications are associated with the CMO_2 and CMO_3 variant options. The best choice among the variant options is clearly CMO_1. In a period of fiscal constraint, it is prudent to manage financial resources in a manner which minimizes cost. Although, the emphasis is directed towards cost minimization, it is equally important to ensure that the quality of delivered health services is maintained.

The opportunity cost associated with the CMO base and variant options are illustrated in Figure 6.47.

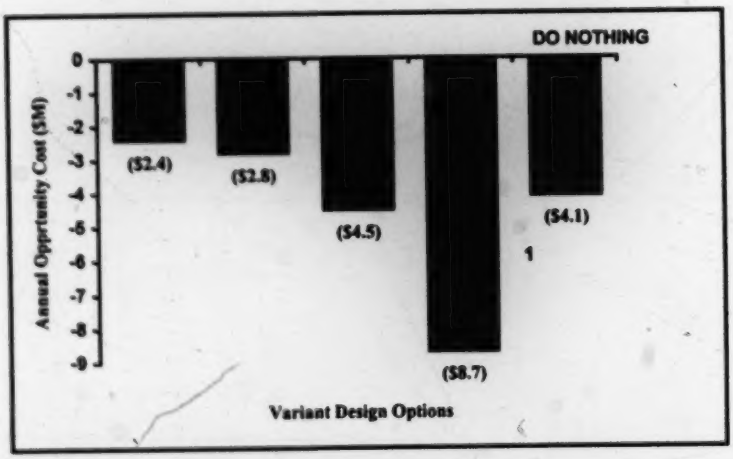


Figure 6.47: Opportunity Cost Gained (Lost) Annually

The opportunity cost illustrated in Figure 6.47 for the base and variant options all result in losses. In other words, all options would require additional resources in the amount shown in Figure 6.47 to ensure the annual target MRI number of exams under each option is attained. It would be unwise under any circumstance to select either of the CMO base or its variant options.

The probability of achieving the expected cost for the base and variant options is given in Table 6.21.

Table 6.21: CMO Expected Cost Per Exam and Associated Probabilities

CMO Options	Expected Cost Per Exam	p (probability of success)
CMO	$767	52 %
CMO_1	$813	53 %
CMO_2	$945	53 %
CMO_3	$1,301	52 %

The results in Table 6.21 indicate the probability of achieving the estimated cost per MRI exam under each CMO option. For example, there is a 52 percent chance of attaining targeted outputs for the base CMO option at a cost of $767 per exam. An increasing pattern in expected cost for the variant options gives rise to the financial severity in delaying full implementation. Figure 6.48 provides an illustration of the risk profiles for the base CMO and its variant options, while a Figure 6.49 shows a more precise cost range for probable outcomes associated with the base CMO option.

From Figure 6.49, the CMO_1 option presents the most cost effective choice at any level of risk when compared to the variant options, CMO_1, CMO_2, and CMO_3 respectively. A noticeable shift in cost is apparent between CMO_2 and CMO_3 which is likely due to escalating costs associated with delaying full implementation by one and five years respectively. Figure 6.49 reveals a more defined range of probable outcomes from which decisions surrounding estimated costs can be fully explored. For example, at LL, there is no chance of attaining target outputs at a cost of $571 per exam. However, at UL, Hospital A is committing to over-spending to avoid risk of failure. In other words, Hospital A is willing incur a cost of $949 per exam in order to achieve targeted outputs. Unfortunately, operating efficiencies are certain to suffer due to inadequate financial resources.

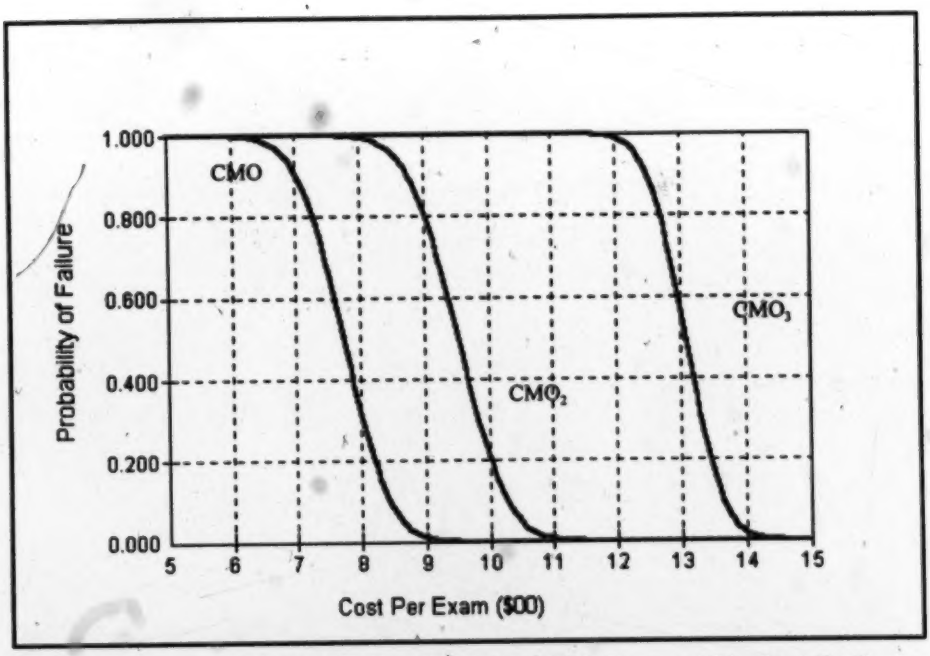


Figure 6.48: Probability of Failure For The CMO Base and Variant Options

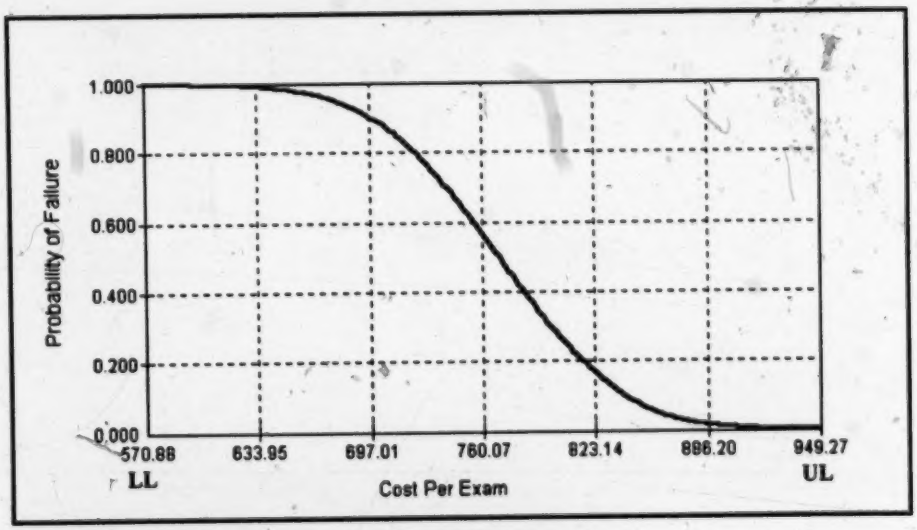


Figure 6.49: Risk of Failure For The CMO_1 Option

6.8 Choice of MRI Design Options

Table 6.22 summarizes the results for each MRI base and its variant design options. The expected cost per exam is given with the probability of achieving this value shown in brackets. Figure 6.50 illustrates these summarized expected cost per exam for the MRI design options

Table 6.22 Results of Structural Design Option Matrix

Design Option	Base Option ($ Per Exam)	1st Variant Option ($ Per Exam)	2nd Variant Option ($ Per Exam)	3rd Variant Option ($ Per Exam)
UES	350 (p=0.53)	400 (p=0.53)	491 (p=0.51)	974 (p=0.51)
CAT	510 (p=0.51)	552 (p=0.51)	661 (p=0.52)	1,069 (p=0.51)
CAR	708 (p=0.49)	736 (p=0.51)	838 (p=0.49)	1,218 (p=0.50)
CPO	753 (p=0.50)	843 (p=0.50)	903 (p=0.51)	1,289 (p=0.51)
LCE	365 (p=0.51)	416 (p=0.52)	513 (p=0.54)	990 (p=0.52)
CAH	471 (p=0.51)	518 (p=0.52)	607 (p=0.53)	1,042 (p=0.52)
CMO	767 (p=0.53)	813 (p=0.53)	945 (p=0.51)	1,301 (p=0.51)

There appears to be an upward trend in the cost of providing MRI exams by examining each of the design option. It can be seen from Figure 6.50 that the MRI design option associated with the lowest cost structure is UES, while the design option with the highest cost structure is CMO. The choice among the most cost effective MRI design options is given in Section 6.8.1.

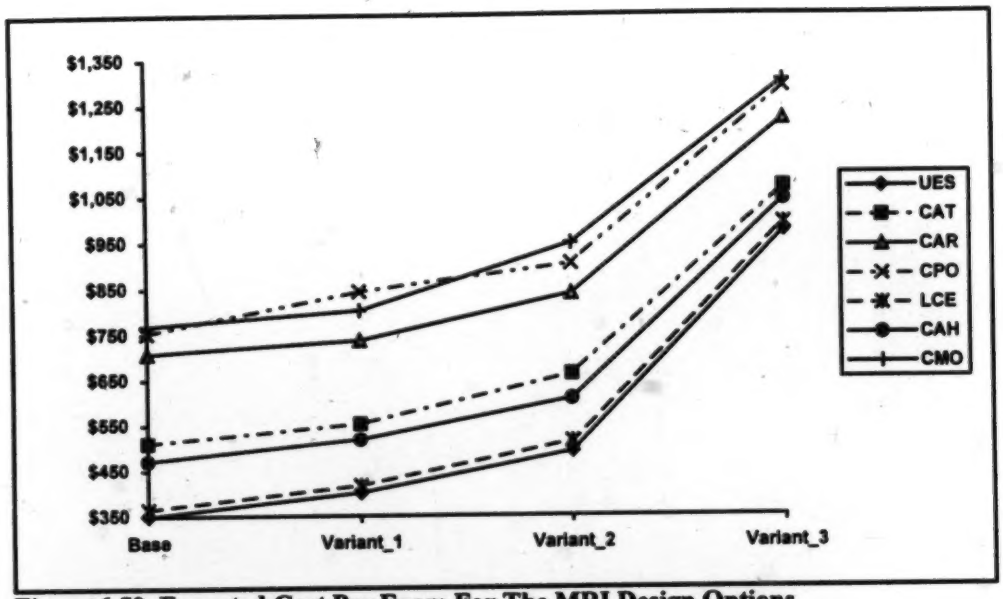


Figure 6.50 Expected Cost Per Exam For The MRI Design Options

6.8.1 Top Three MRI Design Options

The selection among the seven MRI design options to be recommended to Hospital A's management is based on the design option with the least value obtained from equation (29) found in Chapter 3.0. The numerical evaluation for each design option based on equation (29) is presented in Table 6.23, while Table 6.24 ranks these design options.

Table 6.23 Selection of Design Options

Design Option	Base Option ($ Per Exam)	1st Variant Option ($ Per Exam)	2nd Variant Option ($ Per Exam)	3rd Variant Option ($ Per Exam)
UES	-14.35	23.50	76.09	312.76
CAT	85.40	105.98	152.78	359.31
CAR	196.58	196.14	262.88	444.50
CPO	212.00	257.00	277.97	467.11
LCE	14.35	35.18	71.48	310.70
CAH	66.29	84.14	120.79	335.66
CMO	195.99	217.61	298.55	472.99
Do Nothing	217.00	217.00	217.00	217.00

Table 6.24 Ranking Design Options

Option	OC ($)	Option	OC ($)	Option	OC ($)	Option	OC ($)
UES	-14.35	CAH_1	84.14	CAR	198.58	LCE_3	310.70
LCE	14.35	CAT	85.40	CPO	212.00	UES_3	312.76
UES_1	23.50	CAT_1	105.98	CMO_1	217.61	CAH_3	335.66
LCE_1	35.18	CAH_2	120.79	CPO_1	257.00	CAT_3	359.31
CAH	66.29	CAT_2	152.78	CAR_2	262.88	CAR_3	444.50
LCE_2	71.48	CMO	195.99	CPO_2	277.97	CPO_3	467.11
UES_2	76.09	CAR_1	196.14	CMO_2	298.55	CMO_3	472.99
Do Nothing	217.00		217.00		217.00		217.00

The top three MRI design options with the least value given by equation (29) for the base option, beginning with the best one includes UES, LCE, and UES_1. The UES design option is the better choice in the long-term for Hospital A because capital acquisitions are directed towards improving the existing system to provide increased access, improved operating efficiency, and ensure the highest quality in delivered services. The MRI wait list becomes more manageable in among all three design options. The second best choice is the LCE design option. Hospital A can opt to select this option, if it cannot commit the necessary resources to acquire new MRI equipment. Leasing is an effective method to finance capital purchases in the short-term, however, it is costly in the long-term. Hospital A can benefit from this option because it does not have to deplete its capital fund. Instead, it can make monthly lease payments. As a result, it can allocate capital resources to fund required acquisitions elsewhere in the system. Implementing UES_1 is the third most economical choice among the top three design options. This choice is feasible, especially, if Hospital A cannot commit resources towards full implementation today. In light of the current political and economical climate, it is conceivable that decision-makers would prefer to commit partial resources toward the UES_1 design option, so that they can fund smaller capital projects. The benefit of this option is that Hospital A can control or possibly eliminate "bottlenecks" in other parts of the system, thereby enhancing the delivery and quality of health services. For example, capital funding can

be directed towards opening an additional operating theater to perform more hip and knee replacements. Thus, the choice among MRI design option remains largely part of the strategic decision-making process. Hospital A must consider a combination of cost, throughput, process efficiency, and quality of services when deciding whether to select UES, LCE or UES_1 design options.

6.9 Risk Control and Management Plan

Hospital A can develop a strategic plan which effectively controls risk and ensures that targeted outputs are achieved for the MRI system. An important approach to managing risk is to have a cost containment plan which can be developed by carefully designing a costing methodology to capture unit costs. Unit costs are to be divided into variable and fixed costs. Fixed costs represent a significant contribution toward total operating costs. Once the costing data is collected and analyzed, the MRI managers can monitor specific inputs such as cryogen consumption – a liquid medium used in cooling the MRI equipment. Increases in critical inputs can serve as a flag for potential problems in the MRI system. Rising prices in crucial parts for the MRI system can be substantial, therefore, managers must explore the availability of substitute parts. Thus, a detail costing methodology is certain to streamline expenditures and minimize risk.

Furthermore, time and motion study can be used to accurately measure cycle times for an MRI exam. It is conceivable that human resources can be maximized from the results in these studies. In other words, improving patient preparation, and enhancing patient education so that they are aware of the necessary procedures. All of these initiatives are a positive contribution toward effective cost control thereby reducing the risk of not being able to achieve targeted outputs. In fact, data collection is the most objective source of information around which to make effective decisions. Management can devise strategic plans from objective analyses. The result is that Hospital A can improve overall operating efficiency of its MRI system, and at the same time, enhance the delivery and quality of health care services. Enhanced operating efficiency implies that equipment utilization increases and decreases to the MRI wait list are in order.

CHAPTER 7.0

CONCLUSIONS, RECOMMENDATIONS AND FURTHER RESEARCH WORK

In this research study, the author uses mathematical and computer models to solve an MRI system performance and capital budgeting problems in a large teaching hospital. A literature review of existing methodologies to deal with hospital capital budgeting reveal a lack of comprehensive objective analyses in healthcare. However, an additional review is carried out to show how advanced analytical tools can be used to enhance existing capital budgeting practices. Technically feasible and structural options are designed to abstract the MRI system for experimental analysis and productivity improvement. Using functional moment and stochastic modeling techniques, the system performance and cost are modeled and simulated under different technical and economic paradigms.

From the analysis of the VARSIM results, the following conclusions are drawn:

1. The variables medfee, medsal, relstaff, regest, conmed, drugs, and radiology significantly contribute to the total AEC variance for UES, LCE, and CAH design options.

2. The variables medsal, regest, medfee, and supplies significantly contribute to the total AEC variance for the CAT option.

3. The variables charter, accommodation, and meal significantly contribute to the total AEC variance for the CAR option.

4. The variables discounted price and incremental volume significantly contribute to the total AEC variance for the CPO option.

5. The variable price significantly contribute to the total AEC variance for the CMO option.

6. Using the chi-square, K-S and A-D goodness-of-fit tests, the following probability density functions (PDF) were selected to sample the random variability in the following variables.

   - The normal distribution is used to sample the random variability in medfee, medsal, relstaff, conmed, drugs, radiology, and inflation in the UES, LCE, and CAH options; medsal, regest, medfee, and supplies in CAT; CAR: charter, accommodation, and meal in CAR; discounted price and incremental volume in CPO; and price in CMO.

   - The lognormal distribution is used to sample the random variability in regest in the UES option.

   - The triangular distribution is used to sample the random variability in salvage value in the UES, LCE, and CAH options.

From the analysis of the stochastic simulation results, the following conclusions are drawn:

7. The UES, LCE, and UES_1 design options yield the best MRI performance and cost results in decreasing order.

8. Implementation of either of these options can result in an increase in the number of operating hours from 4,725 to 11,907 annually.

9. The annual equivalent cost for the UES, LCE, and UES_1 options are \$4.2M, \$4.3M, and \$4.8M respectively.

10. The cost per exam for the UES, LCE, and UES_1 options are $350, $365, and $400 respectively.

11. The probability of achieving the unit costs associated with the UES, LCE, and UES_1 options are 53 percent, 51 percent, and 53 percent respectively.

12. The annual savings for the UES, LCE, and UES_1 options are $2.6M, $2.4M, and $2.0M respectively.

13. The opportunity cost for doing nothing for the UES, LCE, and UES_1 options are $217, $202, and $167 per exam respectively.

14. The average waiting period for an MRI exam under these three design options is expected to decrease from six to two months.

Based on the findings in this research, the following recommendations and suggestions for further study are made:

1. The UES, LCE, and UES_1 options be given a thorough consideration by Hospital management with the objective of implementing any of these options.

2. Similar studies must be carried out for all segments of the Hospital to ensure efficient and economic operations.

3. Hospital personnel must be trained in the use of these tools for total quality management.

4. The data gathering process and storage must be improved to assist personnel in acquiring enough reliable data for validating these models. This will further help analysts to study system behavior patterns for making informed decisions.

5. A windows-based software package must be developed to run the VARSIM and stochastic models of the structural MRI options in this study. This will allow easy and fast analysis for making decisions.

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APPENDIX I

CAPITAL REQUISITION FORM

The capital requisition form used by Hospital A is shown to illustrate the method employed to analyze capital equipment needs. It is clearly shown that very little objective information is presented in this checklist type of approach used by hospital managers to identify their capital requirements.

Permission to use Capital Requisition Form referenced in Appendix I is given by:

Mr. Diamond Shamji
Capital Accountant
Capital Health Authority
8440 - 112 Street
Edmonton, Alberta
T6G 2B7

Phone: (403) 492-2091

REGISTER NUMBER

CAPITAL EQUIPMENT REQUEST

(PLEASE TYPE)

SECTION I

1. Dept: _____ Date: _____
2. Description of Equipment Requested: _____
3. Estimated Cost _____
4. Suggested Supplier _____ Date Required _____
5. Does this equipment replace existing equipment? Yes ☐ No ☐
6. If yes what is inventory number of replaced equipment: _____
7. Where will new equipment be installed? Dept: _____ Rm Nr. _____
8. Is permanent installation required? Yes ☐ No ☐
9. Will equipment be used in direct contact with patients; Yes ☐ No ☐
   If yes, has this equipment been discussed with Electronics Services? Yes ☐ No ☐
10. Will equipment ever be used outside the ? Yes ☐ No ☐ If yes, where:
11. * Will installation of this equipment affect other departments? Yes ☐ No ☐
    If yes which departments _____
12. If funding is from special grant indicate source: _____
13. Remarks (briefly outline reason for this request):

* IT IS THE RESPONSIBILITY OF THE ORGINATOR OF THIS REQUEST TO ENSURE THAT DEPARTMENTS LISTED AT ITEM 11 ARE AWARE OF EQUIPMENT IMPLICATIONS.
NOTE: SUPPLIER INFORMATION AND EQUIPMENT SPECIFICATIONS HELD BY REQUESTING DEPARTMENT ARE TO BE ATTACHED TO THIS REQUEST

_____
CHAIRMAN/DIRECTOR

SECTION II
PURCHASING

ADVANCE NOTIFICATION ONLY DO NOT HOLD IN EXCESS OF ONE WORKING DAY.

14. REMARKS _____

_____ DATE _____ SIGNATURE

SECTION III
PHYSICAL PLANT

15. Estimated Costs For
    a) Installation _____
    b) Maintenance _____
    c) Energy _____
    d) Special Equipment _____
    e) Other _____
    f) Special Conditions < Clinical / Electrical _____
16. REMARKS: _____

_____ DIRECTOR _____ DATE

SECTION IV
APPROVALS

17. _____ VICE PRESIDENT _____ DATE
18. _____ DIRECTOR OF FINANCE _____ DATE
19. Equip Account _____ Cost _____
    Installation Account _____ Cost _____

SECTION V
PURCHASING

20. Supplier _____
    Price _____
21. Estimated Delivery Date _____
22. Tag Number of Equipment _____
23. Catalogue Number of Equipment _____

3830-03672-15DEC82-MATERIEL MAN. PART 1-PURCHASING, PART 2-DEPARTMENT, PART 3-ACCOUNTING, PART 4-DIVISION

Figure A.1: Capital Request Form Used By Hospital A

APPENDIX II

HORIZON CAPITAL REQUEST WORKSHEET

A worksheet used by Hospital Health Systems is presented to show the capital budgeting steps employed when requesting capital equipment needs. This is a step-by-step approach which is completed by checking appropriate sections in the worksheet.

Capital Investment Decision Guidelines

Clear guidelines relating to the level of documentation and justification required for projects of varying size and scope is as important as the development of evaluation criteria. Although all projects should be ranked according to the criteria, the detail required to support a simple replacement of routine equipment should be significantly less than that required to justify a joint venture such as a free-standing ambulatory surgery centre.

The three (3) established levels of documentation and review for projects greater than $500,000 are:

1. Narrative review. For necessary projects (i.e., those required to meet life or safety code regulation) or replacement or continuation of existing services. Topics to be addressed are reflected in this attached Capital Investment Decision Evaluation Worksheet.
2. Detailed financial analysis with modified narrative review. For projects related to expansion of existing services/technology with a cost between $500,000 and $1,000,000.
3. Extensive analysis. For all services with costs exceeding $1,000,000.

Notes:

- Individual hospitals may elect more restrictive thresholds than the system parameters reflected below.
- Applies to projects initiated at the individual hospital or system level.
- Methodology may be used early in the process to identify issues or concerns relative to a project.

Capital Investment Decision Evaluation Worksheet

Critical/ Measure	Evaluation Yes	No	N/A
I. Mission/Vision			
1. Is consistent with system vision			
2. Is consistent with the hospital vision			
3. Fulfills community need			
a) Hospital is the only alternative in the community			
b) There are several alternatives in the community			
c) There is no need			
4. Impact/effect on the other system affiliates			
a) Negative impact			
b) Positive impact			
c) No impact			
II. Market Position			
5. Generates significant number of inpatient admissions or outpatient visits			
a) 200+ admissions or 2,000 outpatient visits			
b) 100-199 admissions or 1,000-1,999 outpatient visits			
c) 1-99 admissions or 1-999 outpatient visits			
d) No additional utilization			
6. Increases referrals from service area			
a) Market share increases by 10% or more in the three years			
b) Market share increases by 5% to 9% in three years			
c) Market share increases by less than 5% in three years			

Evaluation

Yes No N/A

7. Supports or expands centres of excellence
   a) Market share increases by 10% or more in the three years
   b) Market share increases by 5% to 9% in three years
   c) Market share increases by less than 5% in three years

8. Meets employers' needs:
   a) Meets explicit need of at least one employer
   b) Does not explicitly meet needs of at least one employer
   c) Likely to be viewed negatively by area employers

9. Improves the present quality of service:
   a) Yes, improves the overall care provided
   b) No, neither contributes nor detracts from care delivered

10. Promotes cost-effectiveness:
    a) Cost savings greater than $250,000 by third year
    b) Cost savings from $100,000 to $250,000 by third year
    c) Cost savings of less than $100,000 by third year
    d) Increase annual costs

11. Enhances employee recruitment:
    a) Will enhance work environment
    b) No impact on work environment
    c) Negatively impacts work environment

Evaluation

Yes No N/A

IV. Medical Staff Impact

12. Improves relations with physicians:

a) Yes, directly

b) No, indirectly

c) No

13. Contributes to recruitment and retention of physicians:

a) Yes, contributes to recruitment and retention

b) No, neither contributes nor detracts

c) No, detracts from recruitment and retention

14. Is supported by the Medical Staff:

a) Strong support

b) Neutral

c) Strong opposition

Critical/Measure

V. Financial Impact

15. Is self-supporting

a. Breakdown in first year

b. Breakdown in second year

c. Breakdown in third year

d. Breakdown in after third year

16. Rate of return:

a. Internal rate of return greater than required ROI

b. Internal rate of return equals required ROI

c. Internal rate of return less than required ROI

Evaluation

Yes No N/A

17. Improves payor mix:
    a. Less than 20% Medicare/Medicaid
    b. 20% to 34% Medicare/Medicaid
    c. 35% to 44% Medicare/Medicaid
    d. 45% to 60% Medicare/Medicaid
    e. Over 60% Medicare/Medicaid

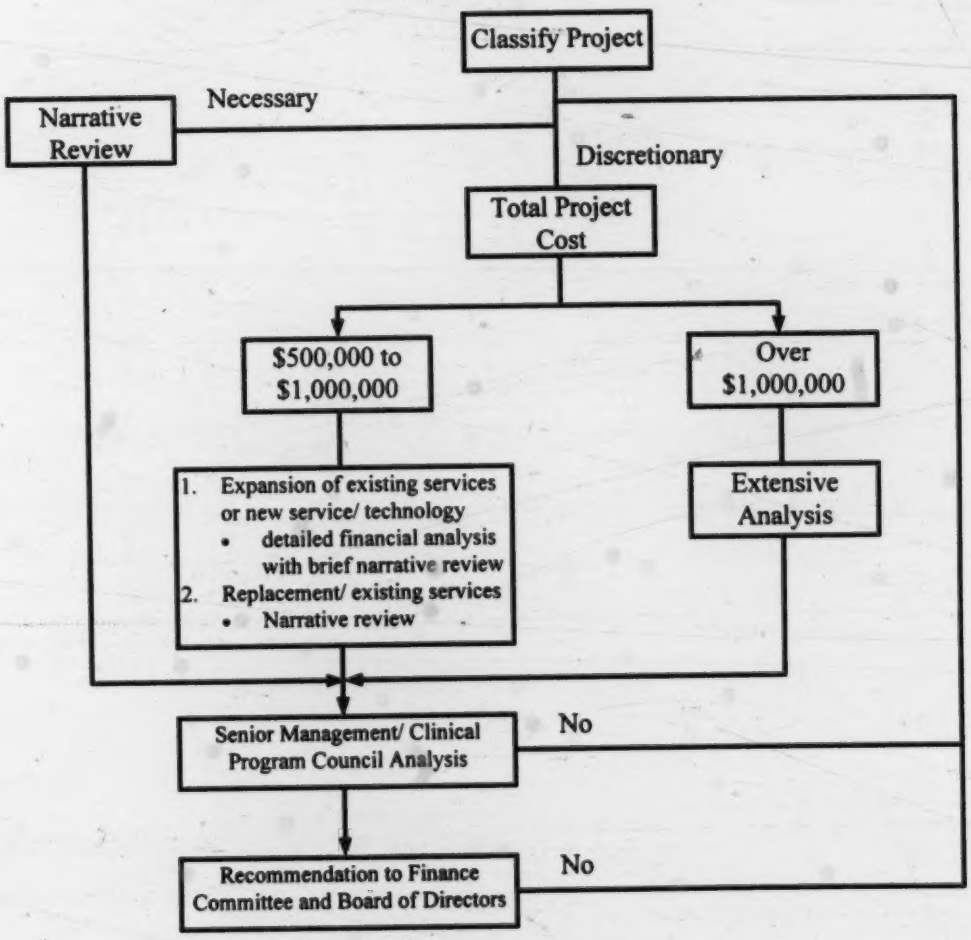

Figure A.2: Schematic of Investment Guidelines

APPENDIX III
HISTORICAL DATA

The historical data gathered from Hospital A is an accumulation of financial and operational information collected over a period of two and one-half years from Hospital A's finance and MRI departments. Each data record represents an aggregation of monthly statistics. There are 32 fields in each record some of which have no entries. The MRI information collected presented tremendous problems while carrying out the analysis in this research for several reasons. First of all, there is inconsistent treatment with respect to data collection. For example, expenses would be accrued over a specified amount of time which resulted in large variations among the data. This led to large coefficients of variation which in this research range from 0.13 to 4.89. To avoid such large variations due to extreme values in the data, it is felt that the interquartile range would be an adequate measure of variability, because it is resistive to influences by extreme values in the data. However, this method could not fully capture an accurate representation of variabilities among some random variables. In such extreme cases, an estimated coefficient of variation of about ten percent is used to represent the variabilities in these random variables. Although, it must be emphasized that actual expected values and variabilities computed from the data are used in this research. There was no attempt to employ methods to massage the MRI data.

Table A.1: Hospital A Cost and Performance Data

Record	Med_Fee	Med_Sal	Rel_Staff	Pre_Pay	Reg_Est	Emp_Ben	Admin	Med_Surg
1	27,400		1,489	1,129	19,587		3,968	177
2	35,100	581	3,306	1,335	19,710		4,803	259
3	33,100	1,200	4,015	1,356	20,271		4,795	102
4	34,200	1,200	5,675	696	20,288		4,965	305
5	30,700	774	4,752	396	20,041		4,533	1,410
6	35,500		2,866	721	18,945		4,643	153
7	30,700		2,908	258	21,421		4,423	-422
8	31,100	22,428	1,871	231	54,894		8,842	163
9	32,300	5,075	2,784	749	25,054	34,543	8,040	74
10	32,100	5,075	1,700	190	31,899	5,192	6,093	141
11	34,700	5,075	2,516	462	15,088	4,939	5,022	208
12	37,400	5,075	2,762	298	26,933	5,645	6,249	24
13	43,285	5,075	2,803	2,502	22,181	5,235	6,487	52
14	39,374	5,075	4,158	293	21,540	5,096	6,043	296
15	35,341	5,075	2,765	165	30,168	5,244	6,301	190
16	38,000	5,075	1,603	183	25,888	5,184	6,075	140
17	35,600	-25,375	3,794	893	48,439	4,147	5,400	185
18	40,000	15,225	2,519	3,701	11,025	3,842	6,105	212
19	37,400	-254	2,094	119	28,105	4,705	5,773	827
20	42,300	-9,896	2,968	750	38,280	3,883	6,263	159
21	39,200		2,983	641	27,490	4,282	5,968	119
22	41,200	-9,643	4,242	4,526	35,310	5,638	6,502	201
23	36,900		2,968	-3,315	26,688	4,968	5,457	247
24	47,650		3,447	615	31,916	5,784	7,153	114
25	41,400		2,063	419	25,465	3,419	5,821	71
26	42,600		3,343	259	28,105	3,918	6,258	108
27	46,600		3,499	521	25,715	6,384	6,617	142
28	38,200		3,788	170	30,568	3,994	6,138	19
29	40,000		3,192	468	31,117	6,070	6,468	172
30	43,500		3,319	337	25,270	4,018	6,116	163

Table A.1: (continued)

Record	ConMed	Drugs	Radiology	Lab	App_Sup	Food	Hou_Kpg	Off_Sup
1		546	4,607				2	117
2		73	3,072				2	27
3		248	5,222					82
4	23,350	-87	5,222				11	28
5		75	4,366					
6	278	49	5,031		8		2	322
7	7,664	465	5,493	89				916
8	-7,664	169	2,405					21
9		104	4,741				3	1,298
10		273	5,373				1	
11		1,150	4,741					28
12	11,556	3	4,741	1,301			2	23
13		6	4,741			2	5	
14		267	5,373		2	8	8	
15		631	6,368			5	1	
16	2,105	378	6,450			4		62
17	3,415	281	1,615			15	1	11
18	4,468	471	6,460			21	3	46
19	2,363	431	3,230		8	4	5	1,030
20	8,141	139	6,461			5	1	
21	2,363	394				5		30
22	5,778	451				7	1	
23	8,045	437						
24	2,335	434	-1,596			24	11	
25		156				8	3	140
26	5,455	361	9,574			16		13
27	5,710	311	4,787			9	2	44
28	4,925	594	3,226			2		2,265
29	4,670	561	4,892			10	3	
30	2,080	361	4,892			7		

Table A.1: (continued)

Record	Comm	Trav_ Exp	Prof_Fee	Edu_Prg	Pur_Svc	Con_Main	Min_Cap	Cap_Eqp
1	412	107			-72			
2	393		0		73			
3	405		0					
4	403	9						
5	422	5,674			23	18,550	100	
6	453		800		165	221		6,426
7	413							
8	411	29			51			
9	425				47	50		
10	416	718				165,633		
11	520				10		331	
12	724	0		688	66	291	845	1,816
13	508				-15	-161		
14	504	12	0		16			
15	425					2,110		
16	39				126			
17	840	880			233	168,489		
18	24	1,073			5			
19	885	37				14		
20	442	35						
21	424	198						
22	427	66			139			
23	24	10						
24	917	44			8	447		
25	425	-27						
26	429	13			143			
27	24	27						
28	462							
29	22	484			142	32		
30	405				20	14,249		

Table A.1: (continued)

Record	Fixed	Revenue	Labour	Total_Cost	Tests	$/Exam	$/IP_Fee
1	48,500	72	53,575	107,970	330	327	83
2	48,500	9,553	64,834	120,771	281	430	125
3	48,500		64,738	119,348	352	339	94
4	48,500		67,024	144,764	330	439	104
5	48,500		61,197	142,789	336	425	91
6	48,500	110	62,675	127,791	352	363	101
7	48,500	1,197	59,711	122,950	274	449	112
8	48,500		119,366	163,451	347	471	90
9	48,500		108,545	163,786	309	530	105
10	48,500		82,249	303,304	350	867	92
11	48,500		67,802	124,094	347	358	100
12	48,500		84,361	159,869	401	399	93
13	48,500		87,568	141,206	372	380	116
14	48,500	-	81,579	136,565	388	352	101
15	48,500	-	85,059	147,147	413	356	86
16	48,500		82,006	139,891	334	419	114
17	48,500		72,899	297,339	376	791	95
18	48,500	(6,545)	82,417	143,831	391	368	102
19	48,500		77,942	135,276	382	354	98
20	48,500		84,547	148,429	426	348	99
21	48,500	(29)	80,564	132,659	372	357	105
22	48,500		87,775	147,358	402	367	102
23	48,500		73,666	130,929	374	350	99
24	48,500	(6,257)	96,566	147,956	489	303	97
25	48,500		78,589	131,961	361	366	115
26	48,500		84,484	149,087	425	351	100
27	48,500		89,336	148,912	450	331	104
28	48,500		82,858	146,870	357	411	107
29	48,500		87,315	146,800	432	340	93
30	48,500	(13)	82,560	153,343	384	399	113

APPENDIX IV
INPUT DATA FOR THE VARSIM AND STOCHASTIC MODELS

The input data are provided for each of the seven structural design options. The data are used to validate the VARSIM and stochastic models. A complete description of the VARSIM and stochastic algorithms are found in Chapter 5.0.

Table A.2: Input Data For UES Model

a) Operating Performance

Annual Exams	
Factor (1.89/ hour)	1.89
Total Operating Hrs/ Week	126
Number of Weeks	50
Total Exams	11,907

b) Operating Cost

	Unit Cost	**Total Cost**
MedFee	100.00	1,190,700
MedSal	5.04	60,011
RelStaff	5.41	64,417
PrePay	1.69	20,158
RegEst	47.29	563,082
Admin	6.01	71,561
EmpBen	7.69	91,565
MedSurg	0.49	5,799
ConMed	8.73	103,948
Drugs	0.88	10,478
Radiology	10.96	130,501
Lab	0.30	3,616
AppSup	0.00	24
Food	0.02	265
HouseKpg	0.01	61
OffSupp	0.64	7,639
GenSupp	2.87	34,131
Comm	1.05	12,480
TravExp	0.72	8,573
ProfFee	0.17	2,081
EducPrg	0.15	1,790
PurServ	0.11	1,285
ConMain	14.85	176,819
Rent,Ins,Util	48.88	$582,014

Table A.2: (continued)

c) Capital Cost

Equipment	
Upgrade Cost (Uc)	$3,000,000
MinCap	3,320
CapEqp	21,443
Estimated Salvage Value	$400,000

d) Economic Indices

Annual Equivalent of Present Sum (A/P,iaf,k)	0.2801

Annual Equivalent of Future Sum (A/F,iaf,k)	0.1562

Uniform Series In An Inflationary Period (P/C,iaf,if,q)	3.7101

Present Equivalent of Future Sum (P/F,iaf,j)	0.7043

Indiv Inflationary Factors	**Category**
Labour Cost	3.0%
Supplies Cost	10.0%
Fixed Cost	5.0%

Planning Horizon (k)	5

Adjusted (iaf)	
Expected Inflation Rate (if)	2.18%
Pre-Tax Rate-of-Return	10.00%
	12.39%

Table A.3: Input Data For CAT Model

a) Operating Performance

Annual Exams	
Factor	4.67
Total Operating Hrs/ Week	80
Number of Weeks	52
Total Exams	19,414

b) Operating Cost

	Unit Cost	**Total Cost**
MedFee	85.00	1,650,190
MedSal	18.77	364,401
RegEst	35.71	693,274
Supplies	13.40	260,148
Rent,Ins,Util	8.18	$158,807
ProfFee	0.17	2,081
EducPrg	0.15	1,790
PurServ	0.11	1,285
ConMain	14.85	176,819
Rent,Ins,Util	48.88	$582,014

c) Capital Cost

Equipment	
Capital Cost	$2,000,000
Estimated Salvage Value	$250,000

Table A.3: (continued)

d) Economic Indices

Annual Equivalent of Present Sum (A/P,iaf,k)	0.2801

Annual Equivalent of Future Sum (A/F,iaf,k)	0.1562

Uniform Series In An Inflationary Period (P/C,iaf,if,q)	3.7101

Present Equivalent of Future Sum (P/F,iaf,j)	0.7043

Indiv Inflationary Factors	**Category**
Labour Cost	3.0%
Supplies Cost	10.0%
Fixed Cost	5.0%

Planning Horizon (k)	5

Adjusted (iaf)	
Expected Inflation Rate (if)	2.18%
Pre-Tax Rate-of-Return	10.00%
	12.39%

Table A.4: Input Data For CAR Model

	Input Data	Growth Factor
Price Per Exam	$650	5%
Volume of Scans	7,182	
Charter Cost	$45	5%
Accommodation	$50	5%
Meal	$30	3%

Table A.5: Input Data For CPO Model

Price Per Exam	$1,000
Discount Price	$750
Fixed Volume	3,591
Incremental Volume	3,591

Table A.6: Input Data For LCE Model

a) Operating Performance

Annual Exams	
Factor (1.89/ hour)	1.89
Total Operating Hrs/ Week	126
Number of Weeks	50
Total Exams	11,907

b) Operating Cost

	Unit Cost	**Total Cost**
MedFee	100.00	1,190,700
MedSal	5.04	60,011
RelStaff	5.41	64,417
PrePay	1.69	20,158
RegEst	47.29	563,082
Admin	6.01	71,561
EmpBen	7.69	91,565
MedSurg	0.49	5,799
ConMed	8.73	103,948
Drugs	0.88	10,478
Radiology	10.96	130,501
Lab	0.30	3,616
AppSup	0.00	24
Food	0.02	265
HouseKpg	0.01	61
OffSupp	0.64	7,639
GenSupp	2.87	34,131
Comm	1.05	12,480
TravExp	0.72	8,573
ProfFee	0.17	2,081
EducPrg	0.15	1,790

Table A.6: (continued)

PurServ	0.11	1,285
ConMain	14.85	176,819
Rent,Ins,Util	48.88	$582,014

c) Capital Cost

Equipment	
Annual Lease Payment	$1,020,000
Estimated Salvage Value	$400,000

d) Economic Indices

Annual Equivalent of Present Sum (A/P,iaf,k)	0.2801

Annual Equivalent of Future Sum (A/F,iaf,k)	0.1562

Uniform Series In An Inflationary Period (P/C,iaf,if,q)	3.7101

Present Equivalent of Future Sum (P/F,iaf,j)	0.7043

Indiv Inflationary Factors	**Category**
Labour Cost	3.0%
Supplies Cost	10.0%
Fixed Cost	5.0%

Planning Horizon (k)	5

Adjusted (iaf)	
Expected Inflation Rate (if)	2.18%
Pre-Tax Rate-of-Return	10.00%
	12.39%

Table A.7: Input Data For CAH Model

a) Operating Performance

Annual Exams	
Factor (1.89/ hour)	1.89
Total Operating Hrs/ Week	76
Number of Weeks	50
Total Exams	7,182

b) Operating Cost

	Unit Cost	**Total Cost**
MedFee	100.00	718,200
MedSal	5.04	36,197
RelStaff	5.41	38,855
PrePay	1.69	12,159
RegEst	47.29	339,637
Admin	6.01	43,164
EmpBen	7.69	55,230
MedSurg	0.49	3,498
ConMed	8.73	62,699
Drugs	0.88	6,320
Radiology	10.96	78,715
Lab	0.30	2,181
AppSup	0.00	14
Food	0.02	160
HouseKpg	0.01	37
OffSupp	0.64	4,608
GenSupp	2.87	20,587
Comm	1.05	7,528
TravExp	0.72	5,171
ProfFee	0.17	1,255
EducPrg	0.15	1,080
PurServ	0.11	775
ConMain	24.62	176,819
MinCap	0.28	2,002
CapEqp	1.80	12,934
Rent,Ins,Util	81.04	$582,014

Table A.7: (continued)

c) Capital Cost

Equipment	
Capital Cost	$2,000,000
Estimated Salvage Value	$250,000

d) Economic Indices

Annual Equivalent of Present Sum (A/P,iaf,k)	0.2801

Annual Equivalent of Future Sum (A/F,iaf,k)	0.1562

Uniform Series In An Inflationary Period (P/C,iaf,if,q)	3.7101

Present Equivalent of Future Sum (P/F,iaf,j)	0.7043

Indiv Inflationary Factors	**Category**
Labour Cost	3.0%
Supplies Cost	10.0%
Fixed Cost	5.0%

Planning Horizon (k)	5

Adjusted (iaf)	
Expected Inflation Rate (if)	2.18%
Pre-Tax Rate-of-Return	10.00%
	12.39%

Table A.8: Input Data For CMO Model

Price Per Exam	$900
Fixed Volume	7,182

APPENDIX V
VARSIM MODELS AND OUTPUT

The VARSIM programs written in the FORTRAN-77 language are provided for each of the seven base structural design options. A brief description of the program's algorithm is provided at the top of each program. These programs are used to provide the output for the functional moment analysis. Each design option is accompanied by its corresponding VARSIM output which identifies the mean, standard deviation, percent bias and percent variance. A detailed description for the VARSIM program can be found in Chapter 5.0.

TABLE A.9: VARSIM FORTRAN Code For The UES Option

```
      DOUBLE PRECISION FUNCTION REC(X,N)
      A USER WRITTEN ROUTINE WHICH RETURNS A DOUBLE PRECISION
      RESULT FROM THE PRECISION ARGUMENTS IN THE VECTOR "X". IT IS
      ASSUMED THAT THE FUNCTION IS DEFINED THROUGHOUT THE
      PRACTICAL SIMULATION RANGE "X(I)+OR-4*SDX(I),I=1,N" AND IS
      SMOOTH ENOUGH THAT NUMERICAL DIFFERENTIATION MAY BE
      CARRIED OUT. IN ADDITION THE CHARACTER*28 STRINGS DEFINING
      THE ARGUMENT NAMES AND UNITS, THE CHARACTER*15 FUNCTION
      RETURN NAME, THE CHARACTER*7 FUNCTION RETURN UNITS , INITIAL
      VALUES FOR "X(I),I=1,N", AND "N" ARE RETURNED ON THE FIRST
      INVOKATION OF "R=REC(X,N)".THE CHARACTER NAMES ARE
      RETURNED VIA THE COMMON BLOCK "FACT" WHOSE ORDER IS
      "FRNM","FRUNTS","FACT(I),I=1,20". THE MAXIMUM NUMBER OF
      ARGUMENTS IN REC IS 20.

      THIS PARTICULAR FUNCTION IS USED TO CALCULATE AN ANNUAL
      EQUIVALENT COST OF AN MRI EXAMINATION. THE ANALYSIS IS
      CARRIED OUT FOR A FIVE YEAR PLANNING PERIOD. IT IS ASSUMED
      THAT NECESSARY UPGRADES ARE PERFORMED IN ORDER TO ENSURE
      ADEQUATE CAPACITY IS MAINTAINED, SO THAT THE WAIT LIST CAN BE
      MANAGED EFFECTIVELY AND EFFICIENTLY. HOURS OF OPERATION
      ARE INCREASED WHICH ALSO RESULTS IN AN INCREASE TO THE
      NUMBER OF MRI EXAMS.
C
C     FORMULA USED IN PERFORMING THE AEC CALCULATION:
C
C     ={[(MEDFEE+MEDSAL+RELSTAFF+PREPAY+REGEST+ADMIN+EMPBEN)
        (P/G,3%,12.39%,5)
C
        +(MEDSURG+CONMED+DRUGS+RADIOLOGY+CONMAIN+OTHER_SUPP)
C     (P/G,10%,12.39%,5)
C     +(FIXED_COST)(P/G,5%,12.39%,5)
C     +CAPITAL_COST](A/P,12.39%,5)-SV(A/F,12.39%,5)}/(TOTAL_EXAMS)

*****************************************************************************
C     X(1) MEDFEE REPRESENTS MEDICAL FEES
C     X(2) MEDSAL REPRESENTS MEDICAL SALARIES
C     X(3) RELSTAFF REPRESENTS RELIEF STAFF SALARIES
C     X(4) PREPAY REPRESENTS SHIFT DIFFERENTIAL PAY
C     X(5) REGEST REPRESENTS STAFF SALARIES
C     X(6) ADMIN COST
C     X(7) EMPBEN REPRESENTS EMPLOYEE BENEFITS
```

TABLE A.9: (continued)

```
C     X(8)  MEDSURG REPRESENTS MEDICAL-SURGICAL SUPPLIES
C     X(9)  CONMED REPRESENTS A COST INCURRED FOR CONTRAST
            MEDIUM
C     X(10) DRUGS
C     X(11) RADIOLOGY REPRESENTS SUPPLIES COST SPECIFIC TO
            RADIOLOGY
C     X(12) CONMAIN REPRESENTS MAINTENANCE CONTRACT FEE
C     X(13) OTHER SUPP REPRESENTS COSTS SUCH AS
            TELECOMM,EDUCAT,ETC
C     X(14) SV, REPRESENTS CURRENT SALVAGE VALUE FOR THE EXISTING
            MRI EQP
C     X(15) FC REPRESENTS FIXED COST
C     X(16) CC, REPRESENTS CAPITAL COST FOR THE UPGRADE AND
            EXISTING EQP
C
      REAL*8 X(*)
      INTEGER*2 N
      CHARACTER*28 FACT(20)
      CHARACTER*15 FRNM
      CHARACTER*7 FRUNTS
      LOGICAL*2 LN
      COMMON /FUNC/FRNM,FRUNTS,FACT
      DATA LN/.FALSE./
      IF(LN)GO TO 1
C
      FACT(1) ='MEDFEE'
      FACT(2) ='MEDSAL'
      FACT(3) ='RELSTAFF'
      FACT(4) ='PREPAY'
      FACT(5) ='REGEST'
      FACT(6) ='ADMIN'
      FACT(7) ='EMPBEN'
      FACT(8) ='MEDSURG'
      FACT(9) ='CONMED'
      FACT(10)='DRUGS'
      FACT(11) ='RADIOLOGY'
      FACT(12) ='CONMAIN'
      FACT(13) ='OTHER_SUPP'
```

TABLE A.9: (continued)

```
      FACT(14) ='SV'
      FACT(15) ='FIXED'
      FACT(16) ='CAPITAL'
      SRNM='UNIT EXAM COST'
      FRUNTS='$/EXAM'
      X(1)  =1190700.D0
      X(2)  =60011.D0
      X(3)  =64417.D0
      X(4)  =20158.D0
      X(5)  =563082.D0
      X(6)  =71561.D0
      X(7)  =91565.D0
      X(8)  =5799.D0
      X(9)  =103959.D0
      X(10) =10474.D0
      X(11) =130501.D0
      X(12) =176819.D0
      X(13) =71945.D0
      X(14) =400000.D0
      X(15) =582014.D0
      X(16) =3000000.D0
      N=INT2(16)
      LN=.TRUE.

1     REC=((((X(1)+X(2)+X(3)+X(4)+X(5)+X(6)+X(7))
     &   *((1-((1+0.03)**5)/((1+0.1239)**5))/(0.1239-0.03)))
     &   +((X(8)+X(9)+X(10)+X(11)+X(12)+X(13))
     &   *((1-((1+0.10)**5)/((1+0.1239)**5))/(0.1239-0.10)))
     &   +(X(15)
     &   *((1-((1+0.05)**5)/((1+0.1239)**5))/(0.1239-0.05)))
     &   +(X(16)))
     &   *(0.1239*(1+0.1239)**5)/((1+0.1239)**5-1)
     &   -X(14)*(0.1239/((1 +0.1239)**5-1)))
     &    /11907
      RETURN
      END
```

TABLE A.10: VARSIM FORTRAN Code For The CAT Option

```
      DOUBLE PRECISION FUNCTION REC(X,N)
      A USER WRITTEN ROUTINE WHICH RETURNS A DOUBLE PRECISION
      RESULT FROM THE PRECISION ARGUMENTS IN THE VECTOR "X".  IT IS
      ASSUMED THAT THE FUNCTION IS DEFINED THROUGHOUT THE
      PRACTICAL SIMULATION RANGE "X(I)+OR-4*SDX(I),I=1,N" AND IS
      SMOOTH ENOUGH THAT NUMERICAL DIFFERENTIATION MAY BE
      CARRIED OUT.  IN ADDITION THE CHARACTER*28 STRINGS DEFINING
      THE ARGUMENT NAMES AND CUNITS, THE CHARACTER*15 FUNCTION
      RETURN NAME, THE CHARACTER*7 FUNCTION RETURN UNITS , INITIAL
      VALUES FOR "X(I),I=1,N", AND "N" ARE RETURNED ON THE FIRST
      INVOKATION OF "R=REC(X,N)".THE CHARACTER NAMES ARE
      RETURNED VIA THE COMMON BLOCK "FACT" WHOSE ORDER IS
      "FRNM","FRUNTS","FACT(I),I=1,20".  THE MAXIMUM NUMBER OF
      ARGUMENTS IN REC IS 20.

      THIS PARTICULAR FUNCTION IS USED TO CALCULATE AN ANNUAL
      EQUIVALENT COST OF AN X-RAY EXAMINATION.  THE ANALYSIS IS
      CARRIED OUT FOR A FIVE YEAR PLANNING PERIOD. IT IS ASSUMED
      THAT AN X-RAY EXAM CWOULD BE USED IN PLACE OF AN MRI, WHEN
      THE MRI IS UNABLE TO PROVIDE TIMELY EXAMS.  ALTHOUGH AN X-
      RAY MAY NOT PROVIDE DETAILED INFORMATION CREGARDING SOFT
      TISSUE ANALYSES, IT CAN STILL PROVIDE USEFUL INFORMATION
      WHICH WILL ENABLE THE PHYSICIAN TO DECIDE IF FURTHER
      INVESTIGATION IS WARRANTED.
      IT IS ANTICIPATED THAT THE NUMBER OF X-RAYS WILL INCREASE
      APPRECIABLY TO ACCOUNT FOR ADDED VOLUMES AS A RESULT OF
      THE CONSTRAINT IMPOSED ON THE MRI SYSTEM.

      FORMULA USED IN PERFORMING THE AEC CALCULATION

      ={[(MEDICAL_SALARIES+REGULAR_SALARIES+INTERPRET_FEES)(P/G,3
      %,C12.39%,C5)
      +(SUPPLIES_COST)(P/G,10%,12.39%,5)+(FIXED_COST)(P/G,5%,12.39%,5)
      +(CAPITAL_COST)+(AVE_COST_MRI*NO_OF_MRI_EXAMS)(P/G,2.18%,
      12.39%,5)]
      *(A/P,12.39%,5)}/(TOTAL_XRAY_EXAMS)

C     X(1)  REPRESENTS MEDICAL SALARIES
C     X(2)  REPRESENTS REGULAR SALARIES (IE,NURSES, TECHNICIANS,
            CLERICAL)
C     X(3)  INTERPRETATION FEES FOR X-RAYS
C     X(4)  SUPPLIES COST
```

TABLE A.10: (continued)

```
C    X(5)  FIXED COST
C    X(6)  CAPITAL COST
C    X(7)  DISCOUNT RATE
C    X(8)  AVERAGE INFLATION RATE
C    X(9)  TOTAL X-RAYS EXAM
C    X(10) PROJECT LIFE
C
     REAL*8 X(*)
     INTEGER*2 N
     CHARACTER*28 FACT(20)
     CHARACTER*15 FRNM
     CHARACTER*7 FRUNTS
     LOGICAL*2 LN
     COMMON /FUNC/FRNM,FRUNTS,FACT
     DATA LN/.FALSE./
     IF(LN)GO TO 1
C
     FACT(1) ='MEDICAL SALARIES'
     FACT(2) ='REGULAR SALARIES'
     FACT(3) ='INTERP FEES'
     FACT(4) ='SUPPLIES COST'
     FACT(5) ='FIXED COST'
     FACT(6) ='CAPITAL COST'
     FACT(7) ='DISCOUNT RATE'
     FACT(8) ='AVERAGE INFLATION RATE'
     FACT(9) ='TOTAL XRAY EXAMS'
     FACT(10)='PROJECT LIFE'
     FACT(11)='AVG INF RATE FOR LABOR'
     FACT(12)='AVG INF RATE FOR SUPPLIES'
     FACT(13)='AVG INF RATE FOR FIXED COST'
     FACT(14)='AVG COST PER MRI EXAM'
     FACT(15)='NO. OF MRI EXAMS REQUIRED'

     FRNM='UNIT EXAM COST'
     FRUNTS='$/EXAM'
     X(1)=366991.D0
     X(2)=698202.D0
     X(3)=1661920.D0
     X(4)=261997.D0
     X(5)=159935.D0
     X(6)=1600000.D0
     X(7)=0.1239
     X(8)=0.0218
```

TABLE A.10: (continued)

```
      X(9)=19552.D0
      X(10)=5.D0
      X(11)=0.03
      X(12)=0.10
      X(13)=0.05
      X(14)=364.D0
      X(15)=6517.D0
      N=INT2(15)
      LN=.TRUE.
C
1     REC=((((X(1)+X(2)+X(3))
     &    *(1-((1+X(11))**X(10))/((1+X(7))**X(10))))/(X(7)-X(11)))
     &    +((X(4))
     &    *(1-((1+X(12))**X(10))/((1+X(7))**X(10))))/(X(7)-X(12)))
     &    +((X(5))
     &    *(1-((1+X(13))**X(10))/((1+X(7))**X(10))))/(X(7)-X(13)))
     &    +X(6)
     &    +((X(14)*X(15))
     &    *(1-((1+X(8))**X(10))/((1+X(7))**X(10))))/(X(7)-X(8))))
     &    *(X(7)*((1+X(7))**X(10))/(((1+X(7))**X(10))-1)))
     &    /X(9)
C
      RETURN
      END
```

Table A.11: VARSIM FORTRAN Code For The CAR Option

```
      DOUBLE PRECISION FUNCTION REC(X,N)
      A USER WRITTEN ROUTINE WHICH RETURNS A DOUBLE PRECISION
      RESULT FROM THE PRECISION ARGUMENTS IN THE VECTOR "X".  IT IS
      ASSUMED THAT THE FUNCTION IS DEFINED THROUGHOUT THE
      PRACTICAL SIMULATION RANGE "X(I)+OR-4*SDX(I),I=1,N" AND IS
      SMOOTH ENOUGH THAT NUMERICAL DIFFERENTIATION MAY BE
      CARRIED OUT.  IN ADDITION THE CHARACTER*28 STRINGS DEFINING
      THE ARGUMENT NAMES AND UNITS, THE CHARACTER*15 FUNCTION
      RETURN NAME, THE CHARACTER*7 FUNCTION RETURN UNITS , INITIAL
      VALUES FOR "X(I),I=1,N", AND "N" ARE RETURNED ON THE FIRST
      INVOKATION OF "R=REC(X,N)".THE CHARACTER NAMES ARE
      RETURNED VIA THE COMMON BLOCK "FACT" WHOSE ORDER IS
      "FRNM","FRUNTS","FACT(I),I=1,20".  THE MAXIMUM NUMBER OF
      ARGUMENTS IN REC IS 20. THIS PARTICULAR FUNCTION IS USED TO
      CALCULATE AN ANNUAL EQUIVALENT COST OF AN MRI EXAMINATION
      BY CONTRACTING OUT SERVICES TO THE ANOTHER HEALTH REGION.
      THE ANALYSIS IS CARRIED OUT FOR A FIVE YEAR PERIOD.
      IT IS ASSUMED THAT THE HEALTH REGION WILL SUFFICIENTLY
      HANDLE CASES NECESSARY TO REDUCE THE CURRENT WAIT LIST. IN
      OTHER WORDS, THE HEALTH REGION WILL WORK JOINTLY WITH THE
      HOSPITAL TO REDUCE THE WAIT LIST BY ACTING AS BUFFER AND
      ACCEPTING OVERFLOWS PATIENTS. PATIENTS SENT TO A NEARBY
      REGION FOR AN MRI EXAM WILL BE PROVIDED WITH MEALS,
      ACCOMODATION, AND TRANSPORTATION AT NO CHARGE.
C
C      *****FORMULA USED IN CALCULATING AEC*****
C     ={[(PRICE_PER_EXAM*VOLUME_OF_SCANS)+(CHARTER_COST)+
      (ACCOMODATION_COST)
      +(MEAL_COST)](P/G,2.18%,12.39%,5)}(A/P,12.39%,5)
C      ******************************************
C
C     X(1) REPRESENTS A CHARGE FOR AN MRI EXAM
C     X(2) REPRESENTS VOLUME OF EXAMS TO BE CARRIED DURING THE
C          YEAR
C     X(3) REPRESENTS CHARTER COST
C     X(4) REPRESENTS ACCOMODATION COST
C     X(5) REPRESENTS MEAL COST
C     X(6) REPRESENTS TOTAL ANNUAL EXAMS PERFORMED OUT-OF-
C          REGION
C
      REAL*8 X(*)
      INTEGER*2 N
```

Table A.11: (continued)

```
      CHARACTER*28 FACT(20)
      CHARACTER*15 FRNM
      CHARACTER*7 FRUNTS
      LOGICAL*2 LN
      COMMON /FUNC/FRNM,FRUNTS,FACT
      DATA LN/.FALSE./
      IF(LN)GO TO 1
C
      FACT(1)='PRICE PER EXAM'
      FACT(2)='TOTAL EXAMS'
      FACT(3)='CAHRTER COST'
      FACT(4)='ACCOMODATION COST'
      FACT(5)='MEAL COST'
      FACT(6)='PROJECT LIFE'
      FACT(7)='AVG INF RATE'
      FACT(8)='DISCOUNT RATE'
      FRNM='UNIT EXAM COST'
      FRUNTS='COST PER EXAM'
      X(1)=650.D0
      X(2)=7182.D0
      X(3)=323190.D0
      X(4)=359100.D0
      X(5)=215460.D0
      X(6)=5.D0
      X(7)=0.0218
      X(8)=0.1239
      N=INT2(8)
      LN=.TRUE.
C
1     REC=((((X(1)*X(2))+X(3)+X(4)+X(5))
     &   *(1-((1+X(7))**X(6))/((1+X(8))**X(6)))/(X(8)-X(7)))
     &   *(X(8)*((1+X(8))**X(6))/(((1+X(8))**X(6))-1)))
     &   /X(2)
      RETURN
      END
```

Table A.12: VARSIM FORTRAN Code For The CPO Option

```
      DOUBLE PRECISION FUNCTION REC(X,N)
      A USER WRITTEN ROUTINE WHICH RETURNS A DOUBLE PRECISION
      RESULT FROM THE PRECISION ARGUMENTS IN THE VECTOR "X".  IT IS
      ASSUMED THAT THE FUNCTION IS DEFINED THROUGHOUT THE
      PRACTICAL SIMULATION RANGE "X(I)+OR-4*SDX(I),I=1,N" AND IS
      SMOOTH ENOUGH THAT NUMERICAL DIFFERENTIATION MAY BE
      CARRIED OUT.  IN ADDITION THE CHARACTER*28 STRINGS DEFINING
      THE ARGUMENT NAMES AND UNITS, THE CHARACTER*15 FUNCTION
      RETURN NAME, THE CHARACTER*7 FUNCTION RETURN UNITS , INITIAL
      VALUES FOR "X(I),I=1,N", AND "N" ARE RETURNED ON THE FIRST
      INVOKATION OF "R=REC(X,N)".THE CHARACTER NAMES ARE
      RETURNED VIA THE COMMON BLOCK "FACT" WHOSE ORDER IS
      "FRNM","FRUNTS","FACT(I),I=1,20".  THE MAXIMUM NUMBER OF
      ARGUMENTS IN REC IS 20.

      THIS PARTICULAR FUNCTION IS USED TO CALCULATE AN ANNUAL
      EQUIVALENT COST OF AN MRI EXAMINATION BY CONTRACTING OUT
      SERVICES TO THE PRIVATE SECTOR. THE ANALYSIS IS CARRIED OUT
      FOR A FIVE YEAR PLANNING PERIOD. IT IS ASSUMED THAT THE
      PRIVATE OPERATOR WILL SUFFICIENTLY HANDLE CASES
      NECESSARY TO REDUCE THE CURRENT WAIT LIST. IN OTHER WORDS,
      THE PRIVATE OPERATOR WILL WORK JOINTLY WITH THE HOSPITAL TO
      REDUCE THE WAIT LIST BY ACTING AS BUFFER AND ACCEPTING
      OVERFLOWS PATIENTS.
C
C     X(1) REPRESENTS A FIXED CHARGE FOR AN MRI EXAM
C     X(2) REPRESENTS A FIXED VOLUME OF EXAMS TO BE CARRIED
           DURING THE YEAR
C     X(3) REPRESENTS A DISCOUNTED PRICE OFFERED AS AN INCENTIVE
           FOR ADDITIONAL VOLUME (I.E.,EXCESS CAPACITY, OVERFLOW)
C     X(4) REPRESENTS AN INCREMENTAL VOLUME OF EXAMS WHICH IS
           OVER AND ABOVE THE FIXED LEVEL
C
      REAL*8 X(*)
      INTEGER*2 N
      CHARACTER*28 FACT(20)
      CHARACTER*15 FRNM
      CHARACTER*7 FRUNTS
      LOGICAL*2 LN
      COMMON /FUNC/FRNM,FRUNTS,FACT
      DATA LN/.FALSE./
      IF(LN)GO TO 1
```

Table A.12: (continued)

```
C
      FACT(1)='FIXED PRICE PER EXAM'
      FACT(2)='FIXED VOLUME PER YR'
      FACT(3)='DISCOUNT PRICE PER EXAM'
      FACT(4)='INCREMENTAL VOLUME PER YR'
      FACT(5)='TOTAL EXAMS PER YR'
      FRNM='UNIT EXAM COST'
      FRUNTS='COST PER EXAM'
      X(1)=1000.D0
      X(2)=3591.D0
      X(3)=750.D0
      X(4)=3591.D0
      X(5)=7182.D0
      N=INT2(5)
      LN=.TRUE.
C
1     REC=((X(1)*X(2))+(X(3)*X(4)))/X(5)
      RETURN
      END
```

Table A.13: VARSIM FORTRAN Code For The LCE Option

```
      DOUBLE PRECISION FUNCTION REC(X,N)
      A USER WRITTEN ROUTINE WHICH RETURNS A DOUBLE PRECISION
      RESULT FROM THE PRECISION ARGUMENTS IN THE VECTOR "X". IT IS
      ASSUMED THAT THE FUNCTION IS DEFINED THROUGHOUT THE
      PRACTICAL SIMULATION RANGE "X(I)+OR-4*SDX(I),I=1,N" AND IS
      SMOOTH ENOUGH THAT NUMERICAL DIFFERENTIATION MAY BE
      CARRIED OUT. IN ADDITION THE CHARACTER*28 STRINGS DEFINING
      THE ARGUMENT NAMES AND UNITS, THE CHARACTER*15 FUNCTION
      RETURN NAME, THE CHARACTER*7 FUNCTION RETURN UNITS , INITIAL
      VALUES FOR "X(I),I=1,N", AND "N" ARE RETURNED ON THE FIRST
      NVOKATION OF "R=REC(X,N)".THE CHARACTER NAMES ARE RETURNED
      VIA THE COMMON BLOCK "FACT" WHOSE ORDER IS  "FRNM",
      "FRUNTS","FACT(I),I=1,20". THE MAXIMUM NUMBER OF ARGUMENTS IN
      REC IS 20. THIS PARTICULAR FUNCTION IS USED TO CALCULATE AN
      ANNUAL EQUIVALENT COST OF AN MRI EXAMINATION. THE ANALYSIS
      IS CARRIED OUT FOR A FIVE YEAR PLANNING PERIOD. IT IS ASSUMED
      THAT NECESSARY UPGRADES ARE PERFORMED IN ORDER TO ENSURE
      ADEQUATE CAPACITY IS MAINTAINED, SO THAT THE WAIT LIST CAN BE
      MANAGED EFFECTIVELY AND EFFICIENTLY. HOURS OF OPERATION
      ARE INCREASED WHICH ALSO RESULTS IN AN INCREASE TO THE
      NUMBER OF MRI EXAMS. IN THIS DESIGN OPTION, LEASE FINANCING IS
      USED TO ACQUIRE CAPITAL ASSETS TO MEET THE CURRENT DEMAND.
      IN SO DOING, FUTURE UPGRADES TO NEWER TECHNOLOGY WILL BE
      POSSIBLE SINCE THE LESSOR ASSUMES OBSOLESCENCE ASSOCIATED
      WITH THE LEASED EQUIPMENT. LEASED EQUIPMENT CAN BE TRADED-
      IN FOR NEWER TECHNOLOGY ONCE THE LEASED TERM IS UP FOR
      RENEWAL, OR ANYTIME EARLIER, DEPENDING ON THE STRUCTRE OF
      THE LEASE CONTRACT.
C
C     X(1)  MEDFEE REPRESENTS MEDICAL FEES
C     X(2)  MEDSAL REPRESENTS MEDICAL SALARIES
C     X(3)  RELSTAFF REPRESENTS RELIEF STAFF SALARIES
C     X(4)  PREPAY REPRESENTS SHIFT DIFFERENTIAL PAY
C     X(5)  REGEST REPRESENTS STAFF SALARIES
C     X(6)  ADMIN COST
C     X(7)  EMPBEN REPRESENTS EMPLOYEE BENEFITS
C     X(8)  MEDSURG REPRESENTS MEDICAL-SURGICAL SUPPLIES
C     X(9)  CONMED REPRESENTS A COST INCURRED FOR CONTRAST
            MEDIUM
C     X(10) DRUGS
C     X(11) RADIOLOGY REPRESENTS SUPPLIES COST SPECIFIC TO
            RADIOLOGY
```

Table A.13: (continued)

```
C    X(12) CONMAIN REPRESENTS MAINTENANCE CONTRACT FEE
C    X(13) OTHER SUPP REPRESENTS COSTS SUCH AS
           TELECOMM,EDUCAT,ETC
C    X(14) SV, REPRESENTS CURRENT SALVAGE VALUE FOR THE EXISTING
           MRI EQP
C    X(15) FC REPRESENTS FIXED COST
C    X(16) CC, REPRESENTS LEASING COST FOR THE UPGRADE
C
     REAL*8 X(*)
     INTEGER*2 N
     CHARACTER*28 FACT(20)
     CHARACTER*15 FRNM
     CHARACTER*7 FRUNTS
     LOGICAL*2 LN
     COMMON /FUNC/FRNM,FRUNTS,FACT
     DATA LN/.FALSE./
     IF(LN)GO TO 1
C
     FACT(1) ='MEDFEE'
     FACT(2) ='MEDSAL'
     FACT(3) ='RELSTAFF'
     FACT(4) ='PREPAY'
     FACT(5) ='REGEST'
     FACT(6) ='ADMIN'
     FACT(7) ='EMPBEN'
     FACT(8) ='MEDSURG'
     FACT(9) ='CONMED'
     FACT(10)='DRUGS'
     FACT(11) ='RADIOLOGY'
     FACT(12) ='CONMAIN'
     FACT(13) ='OTHER_SUPP'
     FACT(14) ='SV'
     FACT(15) ='FIXED'
     FACT(16) ='LEASE PMT'
     SRNM='UNIT EXAM COST'
```

Table A.13: (continued)

```
      FRUNTS='$/EXAM'
      X(1) =1190700.D0
      X(2) =60011.D0
      X(3) =64417.D0
      X(4) =20158.D0
      X(5) =563082.D0
      X(6) =71561.D0
      X(7) =91565.D0
      X(8) =5799.D0
      X(9) =103959.D0
      X(10) =10474.D0
      X(11) =130501.D0
      X(12) =176819.D0
      X(13) =71945.D0
      X(14) =250000.D0
      X(15) =524260.D0
      X(16) =1020000.D0
      N=INT2(16)
      LN=.TRUE.
C
1     REC=((((X(1)+X(2)+X(3)+X(4)+X(5)+X(6)+X(7))
     &   *((1-((1+0.03)**5)/((1+0.1239)**5))/(0.1239-0.03)))
     &   +((X(8)+X(9)+X(10)+X(11)+X(12)+X(13))
     &   *((1-((1+0.10)**5)/((1+0.1239)**5))/(0.1239-0.10)))
     &   +(X(15)
     &   *((1-((1+0.05)**5)/((1+0.1239)**5))/(0.1239-0.05)))
     &   *(0.1239*(1+0.1239)**5)/((1+0.1239)**5-1)
     &   +X(16)-X(14)*(0.1239/((1 +0.1239)**5-1)))
     &    /11907
      RETURN
      END
```

Table A.14: VARSIM FORTRAN Code For The CAH Option

```
      DOUBLE PRECISION FUNCTION REC(X,N)
      A USER WRITTEN ROUTINE WHICH RETURNS A DOUBLE PRECISION
      RESULT FROM THE PRECISION ARGUMENTS IN THE VECTOR "X". IT IS
      ASSUMED THAT THE FUNCTION IS DEFINED THROUGHOUT THE
      PRACTICAL SIMULATION RANGE "X(I)+OR-4*SDX(I),I=1,N" AND IS
      SMOOTH ENOUGH THAT NUMERICAL DIFFERENTIATION MAY BE
      CARRIED OUT. IN ADDITION THE CHARACTER*28 STRINGS DEFINING
      THE ARGUMENT NAMES AND UNITS, THE CHARACTER*15 FUNCTION
      RETURN NAME, THE CHARACTER*7 FUNCTION RETURN UNITS , INITIAL
      VALUES FOR "X(I),I=1,N", AND "N" ARE RETURNED ON THE FIRST
      INVOKATION OF "R=REC(X,N)".THE CHARACTER NAMES ARE
      RETURNED VIA THE COMMON BLOCK "FACT" WHOSE ORDER IS FRNM",
      "FRUNTS","FACT(I),I=1,20". THE MAXIMUM NUMBER OF ARGUMENTS IN
      REC IS 20.

      THIS PARTICULAR FUNCTION IS USED TO CALCULATE AN ANNUAL
      EQUIVALENT COST OF AN MRI EXAMINATION. THE ANALYSIS IS
      CARRIED OUT FOR A FIVE YEAR PLANNING PERIOD. IT IS ASSUMED
      THAT A NEW MRI IS INSTALLED AT ANOTHER HOSPITAL IN THE SAME
      HEALTH REGION. A NEW INSTALLATION ENSURES THAT THE WAIT LIST
      CAN BE MANAGED EFFECTIVELY AND EFFICIENTLY. OPERATING
      HOURS ARE INCREASED WHICH ALSO RESULTS IN AN INCREASE
      TO THE NUMBER OF MRI EXAMS.
C
C     FORMULA USED IN PERFORMING THE AEC CALCULATION
C
      ={[(MEDFEE+MEDSAL+RELSTAFF+PREPAY+REGEST+ADMIN+EMPBEN)
      (P/G,3%,12.39%,5)
C
      +(MEDSURG+CONMED+DRUGS+RADIOLOGY+CONMAIN+OTHER_SUPP)
      (P/G,10%,12.39%,5)
      +FIXED_COST*(P/G,5%,12.39%,5)
      +CAPITAL_COST
      -SALVAGE_VALUE*(P/F,12.39%,5)]*(A/P,12.39%,5)}/(TOTAL_EXAMS)
C
C     **********************************************************************
C
C     X(1)  MEDFEE REPRESENTS MEDICAL FEES
C     X(2)  MEDSAL REPRESENTS MEDICAL SALARIES
C     X(3)  RELSTAFF REPRESENTS RELIEF STAFF SALARIES
C     X(4)  PREPAY REPRESENTS SHIFT DIFFERENTIAL PAY
C     X(5)  REGEST REPRESENTS STAFF SALARIES
```

Table A.14: (continued)

```
C    X(6)  ADMIN COST
C    X(7)  EMPBEN REPRESENTS EMPLOYEE BENEFITS
C    X(8)  MEDSURG REPRESENTS MEDICAL-SURGICAL SUPPLIES
C    X(9)  CONMED REPRESENTS A COST INCURRED FOR CONTRAST
           MEDIUM
C    X(10) DRUGS
C    X(11) RADIOLOGY REPRESENTS SUPPLIES COST SPECIFIC TO
           RADIOLOGY
C    X(12) CONMAIN REPRESENTS MAINTENANCE CONTRACT FEE
C    X(13) OTHER SUPP REPRESENTS COSTS SUCH AS
           TELECOMM,EDUCAT,ETC
C    X(14) PLANNING HORIZON
C    X(15) SV, REPRESENTS CURRENT SALVAGE VALUE FOR THE EXISTING
           MRI EQP
C    X(16) IF, REPRESENTS AVERAGE INFLATION RATE
C    X(17) IAF, REPRESENTS INFLATION ADJUSTED DISCOUNT RATE
C    X(18) FC REPRESENTS FIXED COST
C    X(19) CC, REPRESENTS NEW CAPITAL ACQUISITION
C    X(20) TOTAL EXAMS
C
     REAL*8 X(*)
     INTEGER*2 N
     CHARACTER*28 FACT(20)
     CHARACTER*15 FRNM
     CHARACTER*7 FRUNTS
     LOGICAL*2 LN
     COMMON /FUNC/FRNM,FRUNTS,FACT
     DATA LN/.FALSE./
     IF(LN)GO TO 1
C
     FACT(1) ='MEDFEE'
     FACT(2) ='MEDSAL'
     FACT(3) ='RELSTAFF'
     FACT(4) ='PREPAY'
     FACT(5) ='REGEST'
     FACT(6) ='ADMIN'
     FACT(7) ='EMPBEN'
     FACT(8) ='MEDSURG'
     FACT(9) ='CONMED'
     FACT(10)='DRUGS'
     FACT(11) ='RADIOLOGY'
     FACT(12) ='CONMAIN'
     FACT(13) ='OTHER_SUPP'
```

Table A.14: (continued)

```
      FACT(14) ='SV'
      FACT(15) ='FIXED'
      FACT(16) ='CAPITAL'
      SRNM='UNIT EXAM COST'
      FRUNTS='$/EXAM'
      X(1)  =718200.D0
      X(2)  =36197.D0
      X(3)  =38855.D0
      X(4)  =12159.D0
      X(5)  =339637.D0
      X(6)  =43164.D0
      X(7)  =55230.D0
      X(8)  =3498.D0
      X(9)  =62705.D0
      X(10) =6318.D0
      X(11) =78715.D0
      X(12) =176819.D0
      X(13) =43395.D0
      X(14) =250000.D0
      X(15) =524260.D0
      X(16) =2000000.D0
      N=INT2(16)
      LN=.TRUE.
C
1     REC=((((X(1)+X(2)+X(3)+X(4)+X(5)+X(6)+X(7))
     &   *((1-((1+0.03)**5)/((1+0.1239)**5))/(0.1239-0.03)))
     &   +((X(8)+X(9)+X(10)+X(11)+X(12)+X(13))
     &   *((1-((1+0.10)**5)/((1+0.1239)**5))/(0.1239-0.10)))
     &   +(X(15)
     &   *((1-((1+0.05)**5)/((1+0.1239)**5))/(0.1239-0.05)))
     &   +(X(16)))
     &   *(0.1239*(1+0.1239)**5)/((1+0.1239)**5-1)
     &   -X(14)*(0.1239/((1 +0.1239)**5-1)))
     &    /7,182

      RETURN
      END
```

Table A.15: VARSIM FORTRAN Code For The CMO Option

```
      DOUBLE PRECISION FUNCTION REC(X,N)
C
      THIS PARTICULAR FUNCTION IS USED TO CALCULATE AN ANNUAL
      EQUIVALENT COST OF AN MRI EXAMINATION BY CONTRACTING OUT
      SERVICES TO A MOBILE OPERATOR. THE ANALYSIS IS CARRIED OUT
      FOR A FIVE YEAR PLANNING PERIOD. IT IS ASSUMED THAT THE MOBILE
      OPERATOR WILL SUFFICIENTLY HANDLE CASES NECESSARY TO
      REDUCE THE CURRENT WAIT LIST. IN OTHER WORDS, THE MOBILE
      PERATOR WILL WORK JOINTLY WITH THE HOSPITAL TO REDUCE THE
      WAIT LIST BY ACTING AS BUFFER AND ACCEPTING OVERFLOW
      PATIENTS.
C
C     X(1) REPRESENTS A FIXED CHARGE FOR AN MRI EXAM
C     X(2) REPRESENTS VOLUME OF EXAMS TO BE CARRIED DURING THE
           YEAR
C
      REAL*8 X(*)
      INTEGER*2 N
      CHARACTER*28 FACT(20)
      CHARACTER*15 FRNM
      CHARACTER*7 FRUNTS
      LOGICAL*2 LN
      COMMON /FUNC/FRNM,FRUNTS,FACT
      DATA LN/.FALSE./
      IF(LN)GO TO 1
C
      FACT(1)='PRICE PER EXAM'
      FACT(2)='VOLUME ANNUALLY'
      FRNM='UNIT EXAM COST'
      FRUNTS='COST PER EXAM'
      X(1)=900.D0
      X(2)=7182.D0
      N=INT2(2)
      LN=.TRUE.
C
1     REC=(X(1)*X(2))/X(2)
      RETURN
      END
```

Table A.16: VARSIM Output For UES Option

#	FACTOR	MEAN	STDEV	% BIAS	% VAR
1	MEDFEE	1,190,700	0.00	0.00	0.00
2	MEDSAL	60,011	0.00	0.00	0.00
3	RELSTAFF	64,417	0.00	0.00	0.00
4	PREPAY	20,158	0.00	0.00	0.00
5	REGEST	563,082	0.00	0.00	0.00
6	ADMIN	71,561	0.00	0.00	0.00
7	EMPBEN	91,565	0.00	0.00	0.00
8	MEDSURG	5,799	0.00	0.00	0.00
9	CONMED	103,959	0.00	0.00	0.00
10	DRUGS	10,474	0.00	0.00	0.00
11	RADIOLOGY	130,501	0.00	0.00	0.00
12	CONMAIN	176,819	0.00	0.00	0.00
13	OTHER_SUPP	71,945	0.00	0.00	0.00
14	SV	400,000	0.00	0.00	0.00
15	FIXED	582,014	0.00	0.00	0.00
16	CAPITAL	3,000,000	0.00	0.00	0.00
	TOTAL BIAS IN	0	$/EXAM		
	ESTIMATED	350	$/EXAM		
	STANDARD DEV	0	$/EXAM		

Table A.16: (continued)

#	FACTOR	MEAN	STDEV	% BIAS	% VAR
1	MEDFEE	1,190,700	156,334	0.00	40.48
2	MEDSAL	60,011	6,001	0.00	0.06
3	RELSTAFF	64,417	19,003	0.00	0.60
4	PREPAY	20,158	0.00	0.00	0.00
5	REGEST	563,082	187,506	0.00	57.19
6	ADMIN	71,561	0.00	0.00	0.00
7	EMPBEN	91,565	0.00	0.00	0.00
8	MEDSURG	5,799	580	0.00	0.00
9	CONMED	103,959	10,396	0.00	0.23
10	DRUGS	10,474	1,047	0.00	0.01
11	RADIOLOGY	130,501	26,100	0.00	1.45
12	CONMAIN	176,819	0.00	0.00	0.00
13	OTHER_SUPP	71,945	0.00	0.00	0.00
14	SV	400,000	0.00	0.00	0.00
15	FIXED	582,014	0.00	0.00	0.00
16	CAPITAL	3,000,000	0.00	0.00	0.00
	TOTAL BIAS I	0	$/EXAM		
	ESTIMATED	350	$/EXAM		
	STANDARD DEV	21.9	$/EXAM		

Table A.17: VARSIM Output For LCE Option

#	FACTOR	MEAN	STDEV	% BIAS	% VAR
1	MEDFEE	1,190,700	0.00	0.00	0.00
2	MEDSAL	60,011	0.00	0.00	0.00
3	RELSTAFF	64,417	0.00	0.00	0.00
4	PREPAY	20,158	0.00	0.00	0.00
5	REGEST	563,082	0.00	0.00	0.00
6	ADMIN	71,561	0.00	0.00	0.00
7	EMPBEN	91,565	0.00	0.00	0.00
8	MEDSURG	5,799	0.00	0.00	0.00
9	CONMED	103,959	0.00	0.00	0.00
10	DRUGS	10,474	0.00	0.00	0.00
11	RADIOLOGY	130,501	0.00	0.00	0.00
12	CONMAIN	176,819	0.00	0.00	0.00
13	OTHER_SUPP	71,945	0.00	0.00	0.00
14	SV	250,000	0.00	0.00	0.00
15	FIXED	582,014	0.00	0.00	0.00
16	LEASE PMT	1,020,000	0.00	0.00	0.00
	TOTAL BIAS IN	0	$/EXAM		
	ESTIMATED	365	$/EXAM		
	STANDARD DEV	0	$/EXAM		

Table A.17: (continued)

#	FACTOR	MEAN	STDEV	% BIAS	% VAR
1	MEDFEE	1,190,700	156,334	0.00	40.48
2	MEDSAL	60,011	6,001	0.00	0.06
3	RELSTAFF	64,417	19,003	0.00	0.60
4	PREPAY	20,158	0.00	0.00	0.00
5	REGEST	563,082	187,506	0.00	57.19
6	ADMIN	71,561	0.00	0.00	0.00
7	EMPBEN	91,565	0.00	0.00	0.00
8	MEDSURG	5,799	580	0.00	0.00
9	CONMED	103,959	10,396	0.00	0.23
10	DRUGS	10,474	1,047	0.00	0.01
11	RADIOLOGY	130,501	26,100	0.00	1.45
12	CONMAIN	176,819	0.00	0.00	0.00
13	OTHER_SUPP	71,945	0.00	0.00	0.00
15	SV	250,000	0.00	0.00	0.00
18	FIXED	582,014	0.00	0.00	0.00
19	LEASE PMT	1,020,000	0.00	0.00	0.00
	TOTAL BIAS IN	0	$/EXAM		
	ESTIMATED	365	$/EXAM		
	STANDARD DEV	21.9	$/EXAM		

APPENDIX V

FIITED PROBABILITY DISTRIBUTION FUNCTIONS

The data presented in Appendix III are used to fit probability distribution functions (PDF) to the sensitive random variables identified by the VARSIM analysis. Fitted PDFs are selected based on a combination of goodness-of-fit tests and comparing actual input summary statistics with those from the fitted PDFs. Using actual data, only three design options UES, LCE, and CAH are fitted with PDFs. The remaining four design options which include CAT, CAR, CPO and CMO are fitted with PDFs derived from subjective information supplied by manufacturers and consultants in the healthcare field.

The probability distribution functions (PDF) provided in Table A.18 are obtained by using the Bestfit program. Appendix III contains the data used in producing the fitted PDFs which serve as inputs to the stochastic models. The coefficient of variation for the seven random variables varied from 0.13 to 4.89 which is largely due to the nature of the data. In many instances, there are several gaps in the data followed by an accrual entry to account for these gaps. The result is that a large variation is introduced in the analysis for specific random variables (i.e., medsal, conmed, drugs, and radiology) which are certain to overstate results. To overcome potential biases in the results, a coefficient of variation of 0.10 is used where large variation is found in these specific random variables. The remaining random variables employ actual variances.

Table A.18: PDFs For the UES, LCE and CAH Options

	Probability Distribution Functions						
	Normal		Lognormal		Triangular		
Variable	Mean ($/Exam)	Std Dev ($/Exam)	Mean ($/Exam)	Std Dev ($/Exam)	Min	Most Likely	Max
Medfee	100	13.1	-----	-----	-----	-----	-----
Medsal	5.04	0.54	-----	-----	-----	-----	-----
Relstaff	5.41	1.6	-----	-----	-----	-----	-----
Regest	-----	-----	47.29	15.75	-----	-----	-----
Conmed	8.73	0.87	-----	-----	-----	-----	-----
Drugs	0.88	0.08	-----	-----	-----	-----	-----
Radiology	10.96	4.68	-----	-----	-----	-----	-----
Inflation	0.0225	0.00225	-----	-----	-----	-----	-----
SV (UES)	-----	-----	-----	-----	$300,000	$400,000	$500,000
SV (CAH)	-----	-----	-----	-----	$150,000	$250,00	$350,000

Figure A.3 depicts the distribution for the stochastic variable, Medfee. Medfee is fitted with a normal distribution, where the parameters include an estimated mean = 100, and an estimated standard deviation = 13.1. The value shown along the y-axis indicates the probability of obtaining the results for specific classes of unit costs for Medfee, which are

displayed along the bottom of the x-axis. The x-axis displays the range of cost per unit for Medfee values. Interpretation for the probabilities specified along the y-axis is the same for the remaining fitted input distributions shown below.

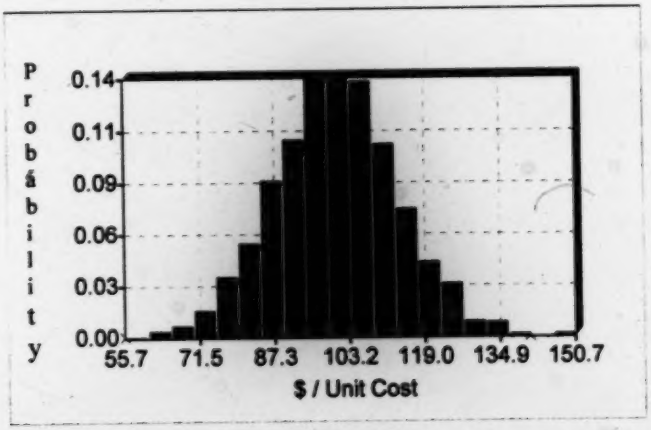

Figure A.3: Input Distribution For Medfee Per Unit Cost

Figure A.4 illustrates the fitted normal distribution for Medsal with a mean of $5.04 per exam and a standard deviation equal to $13.1 per exam. Medsal includes all salaries paid to radiologists who are on staff. For instance, physicians paid by the hospital include residents.

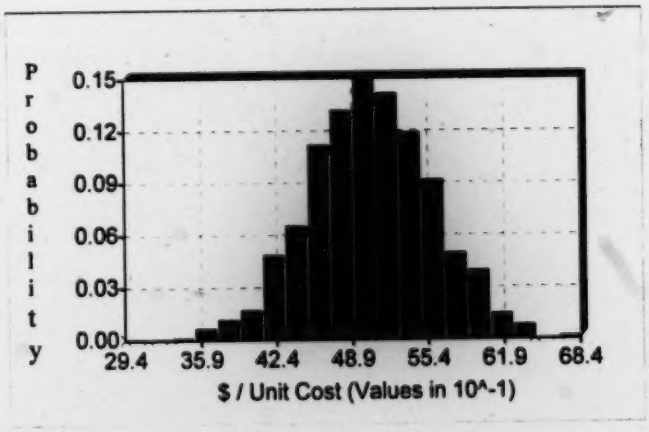

Figure A.4: Input Distribution For Medsal Per Unit Cost

Figure A.5 illustrates the fitted normal distribution for Relstaff with a mean of $5.41 per exam and a standard deviation equal to $1.6 per exam. Relief staff expenditures are incurred by scheduling staff for sick relief, holidays, and overtime.

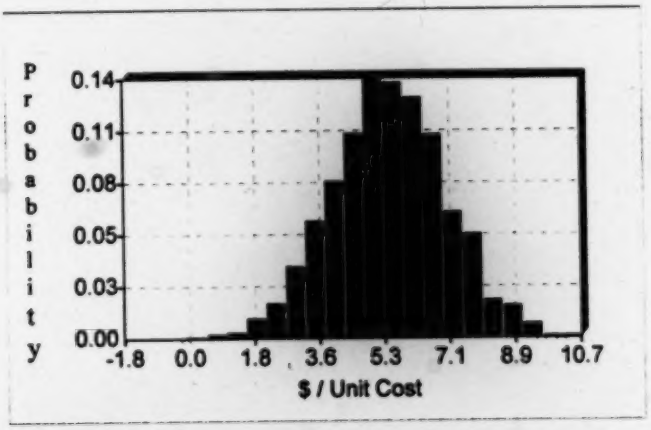

Figure A.5: Input Distribution For Relstaff Per Unit Cost

Figure A.6 illustrates the fitted lognormal distribution for Regest with a mean of $47.29 per exam and a standard deviation equal to $15.75 per exam. Regest includes all salaries paid to non-medical staff which tends to fluctuate during periods of peak demand. The mean is calculated using the formula: $\mu_l = ln\left(\frac{\mu^2}{\sqrt{\sigma^2 + \mu^2}}\right)$, while the standard deviation is determined using the formula: $\sigma_l = \sqrt{ln\left(\frac{\sigma^2 + \mu^2}{\mu^2}\right)}$.

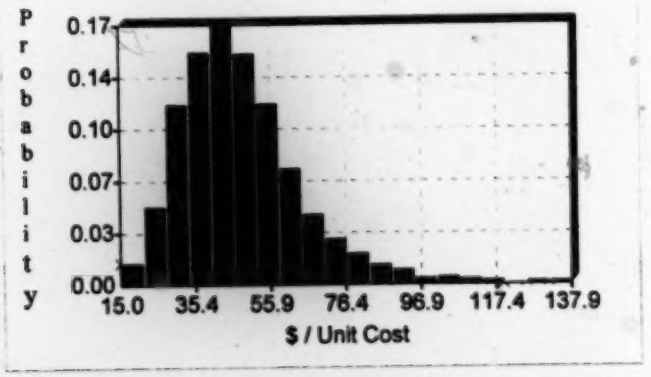

Figure A.6: Input Distribution For Regest Per Unit Cost

Figure A.7 illustrates the fitted normal distribution for Conmed with a mean of $8.73 per exam and a standard deviation equal to $0.87 per exam. Conmed is a contrast medium which is injected into a patient to help Radiologists examine specific body regions.

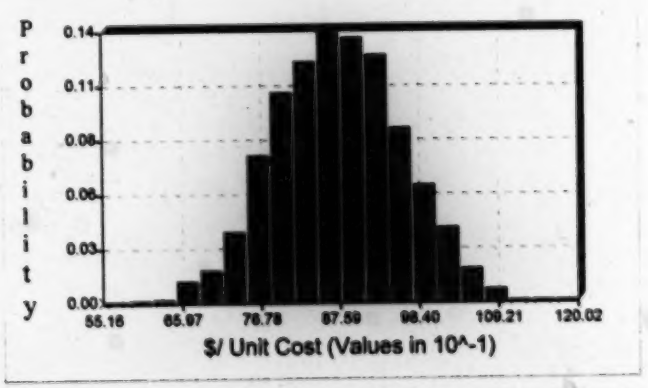

Figure A.7: Input Distribution For Conmed Per Unit Cost

Figure A.8: illustrates the fitted normal distribution for Drugs with a mean of $0.88 per exam and a standard deviation equal to $0.08 per exam. Drugs are used for a variety of reasons. For instance, they are used to sedate some patients prior to entering the MRI's tunnel.

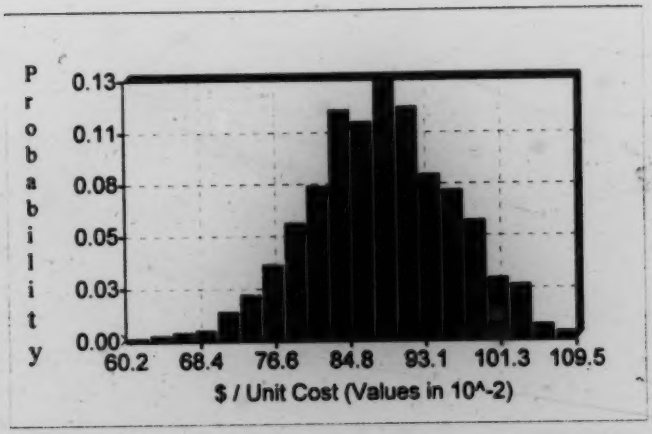

Figure A.8: Input Distribution For Drugs Per Unit Cost

Figure A.9 illustrates the fitted normal distribution for Radiology with a mean of $10.96 per exam and a standard deviation equal to $4.68 per exam. Radiology costs include general supplies such as film material for the MRI.

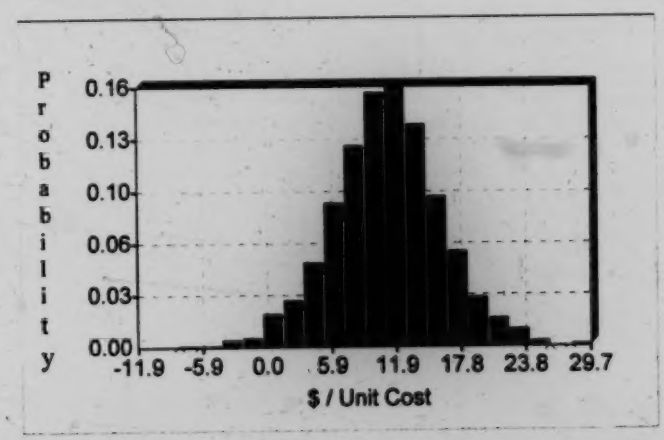

Figure A.9: Input Distribution For Radiology Per Unit Cost

Figure A.9 illustrates the fitted triangular distribution for the estimated salvage value. The estimated parameters include the following -- a minimum value = $300,000, a most like value = $400,000, and a maximum = $500,000.

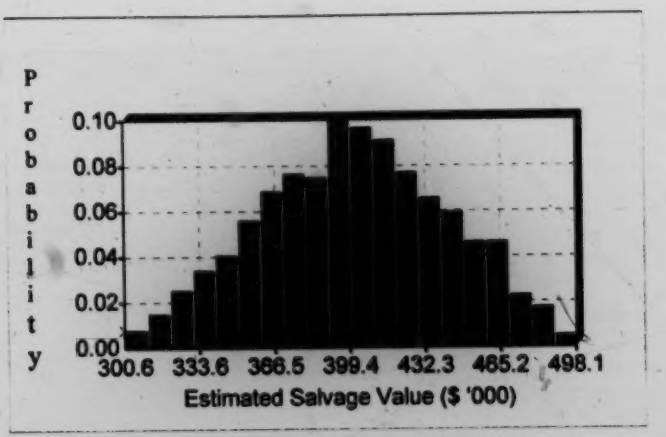

Figure A.10: Input Distribution For Estimated Salvage Value

The CAT option is fitted with a normal and triangular PDF. The input variables medfee, medsal, regest, supplies, and salvage are assumed to have similar PDFs (i.e., normal PDFs) as those found in the UES option which were fitted using real-world data from Appendix III. Also a normal PDF is selected because it is assumed that that the random variables in Table A.19 would behave in a normal-like fashion when sufficiently large random samples are drawn. Since actual data is not available for this option, careful attention must be directed at using this information for decision-making purposes. This particular problem presents a severe limitation regarding the accuracy of the results for the CAT option. A triangular distribution is specified for the salvage value because information provided for this distribution is highly subjective. Information is gathered primarily by communicating with suppliers. Furthermore, a triangular PDF is often the best PDF when information is typically judgmental in nature.

Table A.19: PDFs For The CAT Option

	Probability Distribution Functions				
	Normal		Triangular		
Variable	Mean ($/Exam)	Std Dev ($/Exam)	Min	Most Likely	Max
Medfee	85.00	8.50	-----	-----	-----
Medsal	18.77	1.88	-----	-----	-----
Regest	35.71	3.57	-----	-----	-----
Supplies	13.40	1.34	-----	-----	-----
SV	-----	-----	$150,000	$250,000	$350,000

The input normal PDFs listed in Table A.19 are graphically illustrated below. Figure A.11 depicts the distribution for the stochastic variable Medfee. Medfee is fitted with a normal distribution, where the parameters include an estimated mean = 85.00, and an estimated standard deviation = 8.5. The value shown along the y-axis indicates the probability of obtaining the results for specific classes of unit costs for Medfee, which are displayed along the bottom of the x-axis. The x-axis displays the range of cost per unit for Medfee values. Interpretation for the probabilities specified along the y-axis is the same for the remaining fitted input distributions shown below.

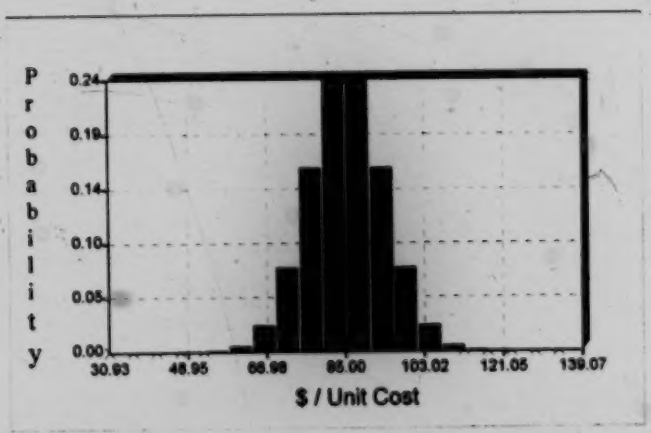

Figure A.11: Medfee Distribution For The CAT Option

Figure A.12 illustrates the fitted normal distribution for Medsal which has a mean of $18.77 per exam and a standard deviation equal to $1.9 per exam. Medsal include all salaries paid to radiologists who are on staff.

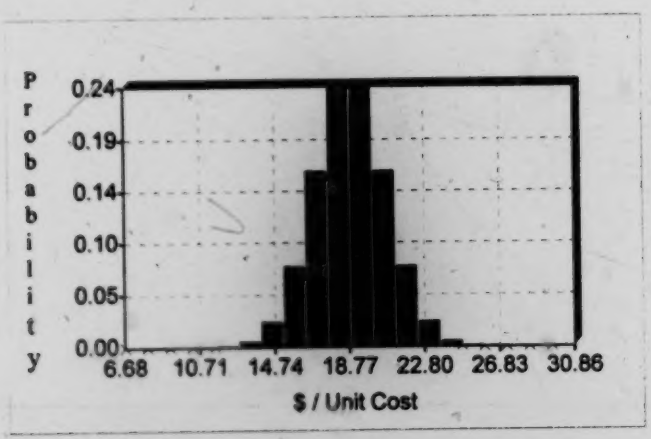

Figure A.12: Medsal Distribution For The CAT Option

Figure A.13 illustrates the fitted normal distribution for Regest which has a mean of $35.71 per exam and a standard deviation equal to $3.6 per exam. Regest include salaries paid to all non-medical staff.

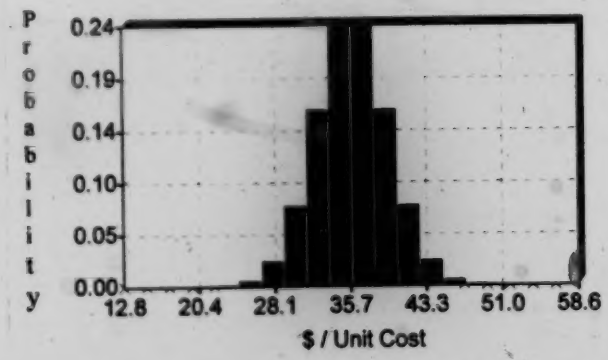

Figure A.13: Regest Distribution For The Cat Option

Figure A.14 illustrates the fitted normal distribution for Supplies which has mean of $13.40 per exam and a standard deviation equal to $1.3 per exam. Supplies account for durable products used in conducting CAT scans such as x-ray film, gowns, syringes and so forth.

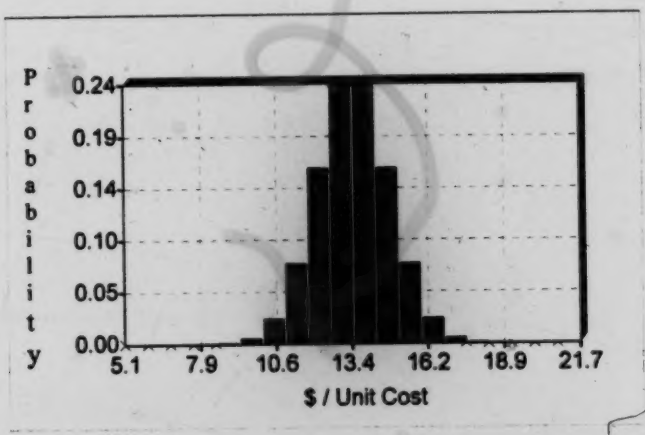

Figure A.14 Supplies Distribution For The Cat Option

Figure A.15 illustrates the fitted triangular distribution for the salvage value. The estimated parameters include the following -- a minimum value = $150,000, a most like value = $250,000, and a maximum = $350,000.

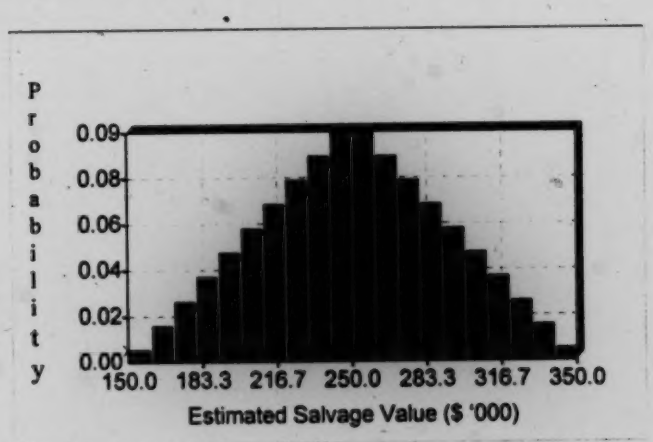

Figure A.15: Salvage Value Distribution For The Cat Option

The normal PDFs listed in Table A.20 are assumed due to unavailable data to accurately describe the random variables shown below. It is assumed that the random variables would behave normally, if drawn randomly from sufficiently large sample sizes. The means for the random variables are estimated from information gathered from chartered bus companies, hotels, and restaurants.

Table A.20: PDFs For The CAR Option

	Probability Distribution Functions	
	Normal	
Variable	Mean ($/exam)	Std Dev ($/exam)
Charter	45.00	4.50
Accommodation	50.00	5.00
Meal	30.00	3.00

The input normal PDFs listed in Table A.12 are graphically illustrated below. The normal PDFs are selected after an insightful discussion with a healthcare consultant and using some preliminary data gathered by telephoning various industries specific to the CAR option. Again, the limitation of these results are due to unavailable data and thus, care should be taken when interpreting and presenting these results.

Figure A.16 depicts the distribution for the stochastic variable Charter. Charter is fitted with a normal distribution, where the parameters include an estimated mean = 45.00, and an estimated standard deviation = 4.5.

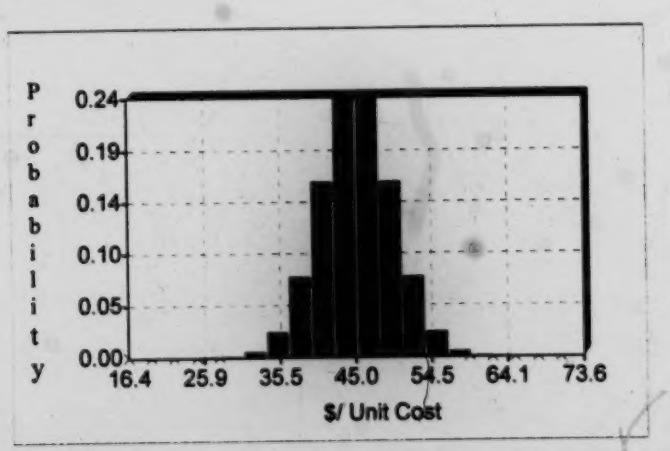

Figure A.16: Input Distribution For Charter Per Unit Cost

Figure A.17 illustrates the fitted normal distribution for Accommodation which has mean of $50.00 per exam and a standard deviation equal to $5.00 per exam. Accommodation includes the cost of an overnight stay for patients receiving an MRI at Health Region B.

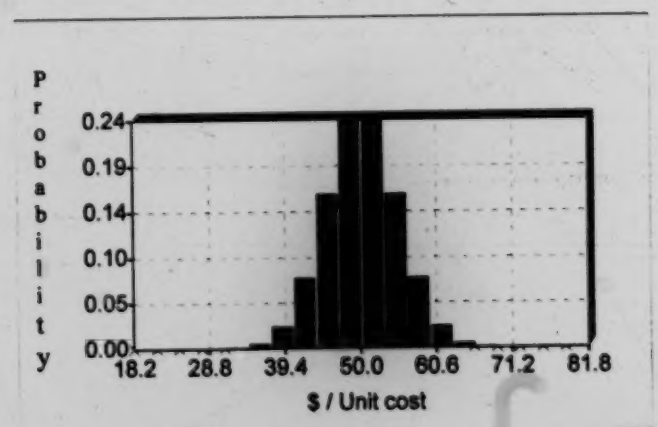

Figure A.17: Input Distribution For Accommodation Per Unit Cost

Figure A.18 illustrates the fitted normal distribution for Meal which has mean of $30.00 per exam and a standard deviation equal to $3.00 per exam. Meal includes the cost of providing lunch and supper for patients awaiting an MRI exam.

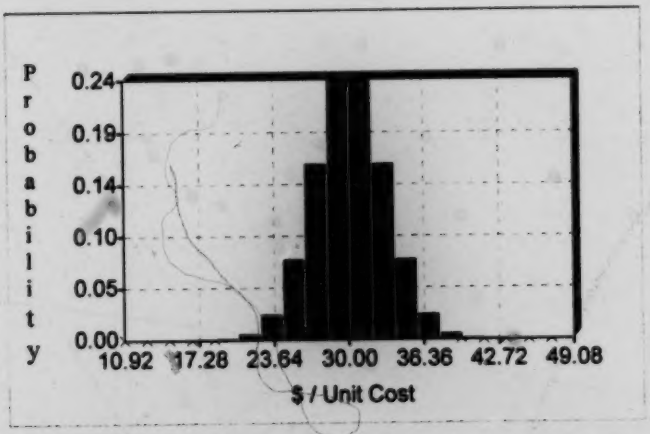

Figure A.18: Input Distribution For Meal Per Unit Cost

The fitted PDFs shown in Table A.21 are assumed due to lack of available data. Once again, it is assumed that the data would behave normally, if samples are randomly drawn and sufficiently large. Estimates for the means of the random variables are gathered from discussion with a local MRI private operator. Although, it should be noted that the discussion regarding pricing levels are simply estimates and therefore not likely to reflect commitment on part of the private operator, until a firm agreement is reached.

Table A.21: PDFs For The CPO Option

	Probability Distribution Functions	
	Normal	
Variable	Mean ($/exam)	Std Dev ($/exam)
Reduced Price	750.00	75.00
Incremental Volume	3,591.00	359.00

The input normal PDFs listed in Table A.21 are graphically illustrated below. These normal PDFs are selected only after discussing the nature of the data with a private

operator. It was felt that the data presented for the CPO option would be accurately depicted using a normal PDF instead of a uniform PDF or triangular PDF. The author inquired about specific estimates for the normal PDF, only after, it was determined that a normal PDF would be accurate as suggested by the private operator. Figure A.19 depicts the distribution for the stochastic variable Reduced Price. Again, the limitation of these results are such that more objective information would be required to place high confidence around the values obtained in the CPO option.

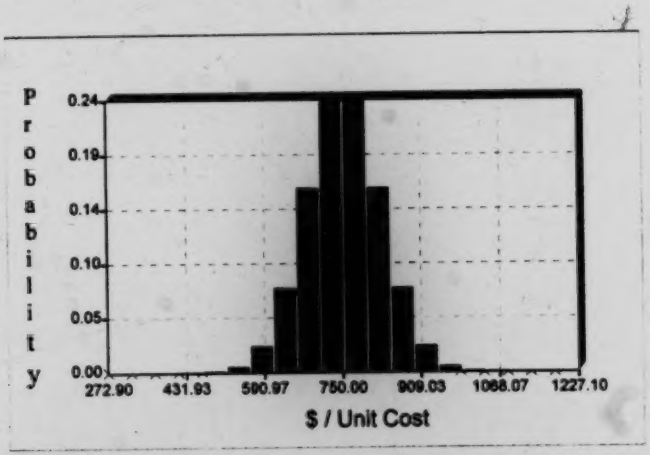

Figure A.19: Input Distribution For Reduced Price

Reduced Price is fitted with a normal distribution, where the parameters include an estimated mean = 750.00, and an estimated standard deviation = 75. The probability distribution for the Incremental Volume is shown below in Figure A.20.

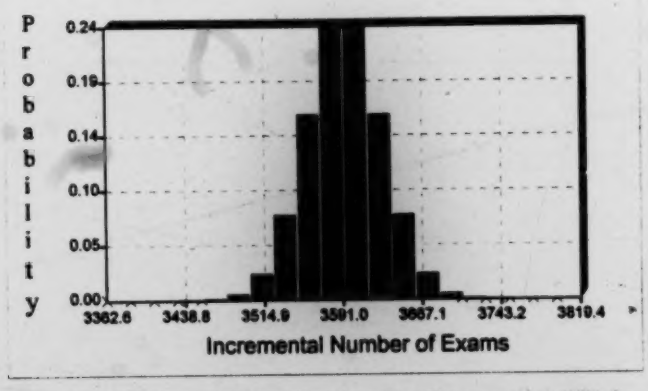

Figure A.20: Input Distribution For Incremental Volume

Figure A.20 illustrates the fitted normal distribution for Incremental Volume which has a mean of 3,591 exams and a standard deviation equal to 359 exams. The random variable Incremental Volume includes exams which exceed the fixed amount required by the private operator. The incremental exams are subsequently processed at a reduced price as an incentive for future contracts.

The normal PDF assumed in Table A.22 is selected as a result unavailable data. However, it is further assumed that the random variable, Price would be normally distributed if sufficiently large samples are randomly drawn.

Table A.22: PDF For CMO Option

	Probability Distribution Functions	
	Normal	
Variable	Mean ($/exam)	Std Dev ($/exam)
Price	900.00	90.00

Figure 21 depicts the distribution for the stochastic variable Price.

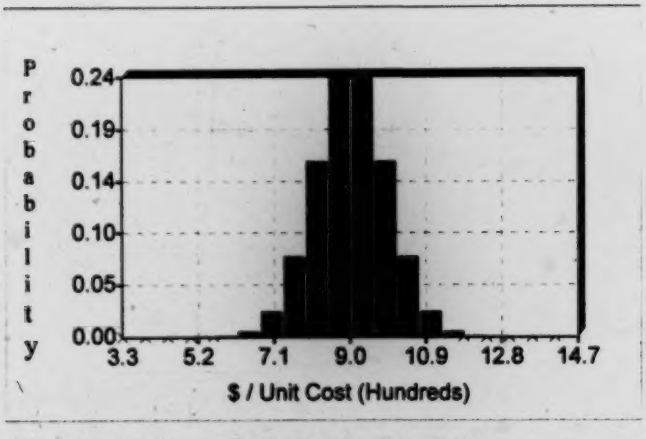

Figure A.21: Input Distribution For Price

The random variable Price is fitted with a normal distribution, where the parameters include an estimated mean = 900.00, and an estimated standard deviation = 90. The normal PDF was used in this option after discussing the other choices of PDFs with an MRI consultant. It was felt that a triangular PDF would not be representative in this, option because estimates for minimum, most likely, and maximum values could not be readily estimated with accuracy. In fact, the consultant suggested that tremendous difficulties are associated with collecting objective data for this option, because it is not a widely used practice. Furthermore, the results shown in this option must be scrutinized and reported with care due to unavailable data. Thus, the limitation of the results presented in this option is the scarcity in obtaining objective data.